Arbeitskreis Quantitative Steuerlehre

Quantitative Research in Taxation – Discussion Papers

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The Productivity Paradox of Corporate Taxation: A Nonlinear Tale of Growth and Constraints

arqus Discussion Paper No. 310
January 2026

www.arqus.info

ISSN 1861-8944

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Abstract

This paper investigates the relationship between corporate income tax rates (CITR) and firm-level productivity growth using AMADEUS data of 304,410 observations from 79,842 European firms from 2006 to 2019. The results imply a robust non-linear relationship: higher CITRs are positively associated with productivity growth for high-productivity firms near the technological frontier and negatively associated with the productivity catch-up of less productive firms. Heterogeneity tests suggest a stronger productivity response to tax rate changes of small and medium-sized enterprises (SMEs) and domestic firms, while I do not find a significant productivity response to tax rate changes for large and multinational firms. The main findings are robust across various productivity estimation methods and model specifications and challenge the conventional view that higher business tax rates have a linear and negative effect on productivity growth. The paper contributes to the ongoing debate about the role of corporate taxation in shaping economic competitiveness and long-term growth.

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1. Introduction

Improving productivity is central to long-run economic growth (Solow, 1957) and firm-level improvement contributes to aggregate productivity (e.g., Acemoglu et al., 2018, Hsieh & Klenow, 2009). While several studies highlight the role of business taxes on growth (e.g., Lee & Gordon, 2005; Johansson et al., 2008; Romer & Romer, 2010; Arnold et al., 2011), there is not robust empirical evidence that higher business taxes reduce macro-economic growth at the country level (Bajardi et al., 2019; ten Kate & Milionis, 2019; Gechert & Heimberger, 2022; Kawano et al., 2025). At the micro level, evidence on the productivity effects of business taxation is sparse and often indirect, typically operating by the effect of business taxation on investments, R&D expenses of firm entr y (Hall & Jorgenson, 1967; Auerbach, 1983; King & Levine, 1993; Bencivenga et al., 1995; Da Rin et al., 2011; Chen et al., 2017; Mukherjee et al., 2017).

More recently, several studies find that higher corporate income tax rates (CITR) may slow down the catch-up of low-productivity firms toward industry leaders (e.g., Vartia, 2008; Gemmell et al., 2018; Bournakis & Mallick, 2018; Romero-Jordán et al., 2020). In addition, the findings of Liu et al. (2022) and Fang et al. (2024) suggest that lower tax burden might have a positive effect on productivity levels by affecting investment and R&D. Yet, the direct relationship between corporate income tax rates and firm productivity growth particularly for high-productivity firms closed to the technological the frontier is still unclear and neglected in previous research. Moreover, recent advances in productivity measurement remains underutilized in the literature (Van Beveren, 2012; De Loecker & Goldberg, 2014), raising concerns about the robustness of earlier findings.

This paper seeks to address these research gaps using a panel dataset of 304,410 firm–year observations from 79,842 European firms from 2006 to 2019. I investigate how CITR relates to average firm-level total factor productivity (TFP) growth and how this relationship varies with the firms' distance to the frontier. Baseline TFP is estimated with Wooldridge's (2009) one-step proxy estimator and then validated with alternative estimators from Ackerberg et al. (2015), Levinsohn and Petrin (2004), Olley and Pakes (1996), and naïve ordinary least squares (OLS). For research design, the empirical model builds on the TFP catch-up framework of Griffith et al. (2009) applied to taxation by Vartia (2008), Arnold et al. (2011), Gemmell et al. (2018), and Romero-Jordán et al. (2020). I extend the model to include both the CITR and its interaction with the firm's TFP gap relative to the frontier, defined as the top 5% of the within-country-industry-year TFP distribution. This approach isolates tax–productivity relationships for more productive firms at the frontier with less productive firms lagging behind. The baseline tax measure is the statutory CITR. I also conduct heterogeneity tests that contrast large firms with small and medium-sized enterprises (SMEs), and domestic with multinational enterprises (MNEs) to explore how firm characteristics affect the association of the CITR and productivity growth. Note that rather than testing formal convergence concepts, such as β-or σ-convergence (Barro & Sala-i-Martin, 1991; Bernard & Durlauf, 1995), the study concentrates on three core inquiries: (i) the relationship between CITR and firm productivity growth of the more productive firms, (ii) how CITRs relate to the speed of productivity catch-up of the less productive firms, and (iii) how these dynamics vary by firm size and multinational versus domestic firms.

The main findings are as follows. On average, CITR are not significantly associated with firm productivity growth if the productivity level of firms is not considered. However, if I allow for different tax associations for firms with high and productivity levels compared to their country-industry peers, I find a non-linear relationship. While CITR are positively associated with productivity growth of highly productive firms, they are negatively associated with productivity growth of the less productive firms. While the second finding aligns with prior research (e.g., Arnold et al., 2011; Gemmell et al., 2018), the positive association of tax rates for the more productive firms is a new insight.

Theoretically, this positive relationship could be attributed to several potential mechanisms. (1) Acemoglu et al. (2018) argue in a theoretical model that corporate taxation can be an efficient mechanism to separate less productive firms out of the market. (2) Higher tax revenues can be used to generate public goods with positive spillovers on productivity growth of firms, such as public spending on education or research and development (e.g., Abiad et al., 2016). (3) As documented by Eichfelder et al. (2023), higher tax rates suggest that firms will reduce their investment volumes but also increase the quality of their investments. This might especially favor highly productive firms.

Quantitatively, my empirical findings suggest that a 1-percentage-point increase in the statutory CITR is associated with a 0.34% increase in TFP growth for top 5% firms at the productivity distribution, reduces to a association 0.051% for a firm with median productivity and results in a reduction of TFP growth by 0.41% for firms at the lower 5% percentile of the productivity. Furthermore, the association of the CITR and productivity growth is more pronounced for SMEs and domestic firms, while I do not find significant associations of the CITR and productivity growth for large and multinational firms. The baseline results are robust to (a) alternative fixed-effects structures, (b) multiple measures of TFP, (c) excluding tax-haven observations, (d) controlling for personal income tax, and (e) alternative definitions of the frontier.

This paper makes several notable contributions to the existing literature and policy discussion. First, by integrating a Griffith et al. (2009) catch-up model with a direct tax term, the study provides a novel framework to understand the relationship between CITR and TFP growth across frontier and non-frontier firms. The negative association between the CITR and productivity catch-up confirms previous evidence. However, the identification of a non-linearity and a positive relationship for the more productive firms is new and helps to explain the mixed evidence regarding the average effects of corporate taxation on productivity (e.g., Liu et al., 2022; Eichfelder et al., 2023). This frontier–laggard decomposition explains why average estimates can differ in sign depending on sample composition.

Second, beyond the well-studied channels that tax liabilities constrain investment and financial capacity, particularly for firms facing financial constraints, the paper documents a positive near-frontier relationship between CITR and TFP growth. This result supports theoretical arguments on the mechanism that higher taxes can foster the productivity gains such as improved investment quality and optimizing resource allocation.

Third, the analysis establishes methodological robustness by applying multiple productivity measurement techniques. By comparing results across these methods, the analysis demonstrates that the relationship between CITR and productivity growth is consistent and irrespective of a specific estimator. This strengthens the validity of the study's findings within the framework established by Griffith et al. (2009).

In terms of policy relevance, CITR appears neutral or even positive at the frontier while slowing followers' convergence. The net effect can intensify pre-existing productivity disparities discussed in recent studies (e.g., Iacovone & Crespi, 2010; Hartmann et al., 2021). This underscores a policy trade-off between reducing disparities in competition and promoting growth. The stronger responses among SMEs and domestic firms, relative to large firms and MNEs, suggest a targeted tax design that limits disproportionate burdens on constrained firms rather than a one-size-fits-all rate.

The remainder of this paper is organized as follows. Section 2 reviews the related literature and develops hypotheses for the empirical analysis. Section 3 details the empirical methodology, while Section 4 provides information on the data and descriptive statistics. Section 5 presents the empirical results and robustness checks. Finally, Section 6 concludes.

2. Related Literature and Hypotheses

2.1 Corporate Income Tax and Productivity Growth

Prior research identifies several channels through which higher business taxes or weaker tax incentives may reduce input uses, and in turn productivity growth. In neoclassical investment models, higher corporate tax burdens raise the user cost of capital and discourage new investments (e.g., Jorgenson, 1963; Hubbard, 1998; Devereux & Griffith, 2003). This dampening effect applies to both tangible capital (Hall & Jorgenson, 1967; Hassett & Hubbard, 2002) and intangibles (e.g., R&D and intellectual property, as suggested by Hall & Van Reenen, 2000), thereby impeding technological adoptions and productivity growth. In addition, higher tax rates can impose financial constraints and the reduction of post-tax incomes would intensify the moral hazard between external creditors and firms, weakening the firm's ability to borrow (Frazzari et al., 1988; Holmström & Tirole, 1997). Together, higher tax burdens impede the ability of firms to finance productivity-enhancing investments.

Regarding labor input, higher business taxes can reduce labor demand and employment (Bettendorf et al., 2009; Zirgulis & Šarapovas, 2017; Mukherjee & Badola, 2023). Tax incidence theory further suggests that part of corporate tax liabilities is shifted to employees via lower wages. However, the empirical evidence is mixed (e.g., Arulampalam et al., 2012; Liu & Altshuler, 2013; Eichfelder and Nguyen, 2025; Gstrein et al., 2025). A recent meta study of Knaisch and Pöschel (2024) does not find robust evidence that higher corporate income taxes result in lower wages.

In line with these more nuanced findings on corporate tax incidence in the more recent literature, there is also no robust evidence that higher corporate income taxes reduce economic growth (e.g., Baiardi et al., 2019; ten Kate & Milionis, 2019; Gechert & Heimberger, 2022; Kawano et al., 2025). While higher corporate tax burdens generally reduce investment volumes (Becker et al., 2012; Eichfelder et al., 2025), evidence suggests they can also shift the quality of investment. For example, the expiration of bonus depreciation in Germany increased investment quality, implying a selection effect at higher user cost (Eichfelder et al., 2023). More broadly, tax policy shapes the quality of capital purchased and the quality of FDI, not only the quantity (Goolsbee, 2004; Becker et al., 2012), with theory predicting higher thresholds under higher user costs (Abel & Eberly, 1994; Barry, 2024).

Corporate income taxes are also correlated with public spending that has a positive effect on productivity growth. According to Gomes and Pouget (2008), a 15% cut in the CIT rate is linked to a 0.6–1.1% of GDP reduction in public investment across OECD countries. Findings at the macro-level show that public investment in infrastructure and human capital raises output and supports productivity (Abiad et al., 2016; Eberts & McMillen, 1999; Duranton & Puga, 2004). Micro evidence likewise links transport infrastructure to higher firm-level TFP (Kailthya & Kambhampati, 2022). Moreover, endogenous-growth models show that capital taxation can raise growth when revenues finance productive expenditures (Jones et al., 1993; Aghion et al., 2016). Finally, because R&D creates knowledge spillovers, R&D tax subsidies help correct underinvestment and support technological progress and productivity (Arrow, 1962; Romer, 1986, 1990; Grossman & Helpman, 1991).

2.2 Corporate Income Tax and Productivity: Frontier vs. Catch-Up Effects

Prior theoretical and empirical work also shows that the effects of corporate tax differ substantially across firm types. For small and domestic firms, which often operate with narrower profit margins and rely more on external financing (Beck et al., 2008), high CITR significantly reduce their internal funds and borrowing capacity for reinvestment. They also face disproportionate compliance costs with higher administrative expenses relative to sales than larger firms (OECD, 2009, 2015). This compliance cost thereby exacerbates the tax burden for small firms under high tax regimes and further divert their scarce resources from growth-oriented activities. By contrast, large and multinational enterprises typically possess greater market power, enabling them to shift a greater portion of the tax burden to consumers or employees (Fuest et al., 2018; Hager & Baines, 2020). They also benefit from economies of scale in tax planning and, when feasible, international profit shifting (Janský & Palanský, 2019; OECD, 2017), allowing them to sustain productivity-enhancing investments even under higher tax burdens. Other studies show that large and multinational firms tend to operate at higher productivity levels and are more often situated near the technological frontier (To et al., 2018; OECD, 2025).

Acemoglu et al. (2018) develop a model predicting differential tax effects by distance to the technological frontier. In their model, access to qualified labor is central for productivity growth, especially via R&D. With R&D generating positive spillovers, firms tend to underinvest in R&D and overinvest in routine operations, leaving too little skilled labor in high-productivity firms too much in less productive firms (Hamano & Zanetti, 2022). A welfare-maximizing planner would reallocate skilled labor from low-type firms to high-type firms (Jovanovic, 1982; Hopenhayn, 1992; Acemoglu et al, 2018). Acemoglu et al. (2018) argue that business taxes are an efficient mechanism to increase the number of market exits of the less productive and innovative firms and thus to redistribute high-skilled labor from low-type to high-type firms. While simulations support these mechanisms, there is not empirical evidence on the reallocation mechanism suggested by Acemoglu et al. (2018).

Empirical evidence on how corporate income taxation affects firm-level productivity growth remains limited. Most recent studies focus on convergence speeds with which the low productive firms catch-up to industry leader, but do not account for the direct tax effect on productivity growth. This research generally finds that higher taxes slow convergence (e.g., Arnold et al., 2011; Gemmell et al., 2018; Romero-Jordán et al., 2020), implying a disproportionate impact on laggards relative to frontier firms. In addition, some studies analyze the effect of business taxes on productivity levels an find some support for a negative average tax effect (Galindo & Pombo, 2011; Liu et al., 2022; Fang et al., 2023). Only a few papers explicitly compare responses to business taxation by the productivity level of firms. Bournakis & Romero-Jordán (2024) document stronger R&D and exporting responses among low-TFP firms, and Bartolini (2018) reports lower effective taxation among frontier firms.

Building on these theoretical and empirical perspectives, Table 1 summarizes the mechanisms through which CITR may relate to firm productivity growth. Guided by these channels, I formulate two differential hypotheses for firms at/near the frontier and for firms further behind:

H1: Higher CITR are positively associated with a higher productivity growth for firms closer to the production frontier.

H2: Higher CITR are negatively associated with a lower productivity catch-up rate of low-productivity firms.

Table 1 – The relationship of CITR and Firm Productivity Growth

Mechanism	Expectation	Implication for TFP growth	References
User cost of capital ↑	Raises required return; depresses investment	–	Hall & Jorgenson (1967); Auerbach (1983)
Liquidity constraints ↑	Lowers internal funds and borrowing capacity	–	King & Levine (1993); Bencivenga et al. (1995)
Investment quality ↑	Screens out low-return projects	+	Eichfelder et al. (2023)
Competition/selection ↑	Squeezes out low-productivity firms	+	Acemoglu et al. (2018); Melitz (2003); Hopenhayn (1992)
Public investment ↑	Finances infrastructure and human capital	+	Agion et al. (2016); Barro (1990); Aschauer (1989)

3. Methodology

3.1 Firm Productivity Measurement

I measure firm-level TFP based on a value-added production function as follows

$$y_{it} = \alpha_0 + \gamma_k k_{it} + \gamma_l l_{it} + \rho_{it} + \varepsilon_{it}, \qquad (1)$$

where y_{it} represents the logarithm of value-added output, while k_{it} and l_{it} capture the logarithm of capital and labor input, respectively. The unobserved term ω_{it} after accounting for all input contributions reflects total factor productivity (TFP). The term ε_{it} is white noise that controls idiosyncratic error.

Because firms choose inputs partly in response to their own productivity, these inputs are typically correlated with unobserved productivity shocks. Thus, naïve OLS estimates of the production function are biased. To address this issue, I adopt the Wooldridge (2009) one-step proxy estimator as the baseline and assess robustness using Olley–Pakes (1996), Levinsohn–Petrin (2004), and Ackerberg–Caves–Frazer (2015).

All four methods share the same intuition: they exploit an observable firm decision that co-moves with productivity, such as investment or intermediate inputs, as a proxy for the unobserved productivity shock ρ_{it}, and then use this structure to recover the production-function elasticities. They differ in the proxy employed and in the identification strategy for the input elasticities (see Appendix A for implementation details).

Olley and Pakes (1996) use investment as a proxy for productivity shocks and relies on firms' investment decisions to identify coefficients. Levinsohn and Petrin (2004) replace investment with intermediate inputs (e.g., materials) to relax the requirement of strictly monotonic investment. Ackerberg, Caves, and Frazer (2015) refines the proxy approach by using a more flexible timing structure for input choices that allows for dynamic labor decisions. In contrast, Wooldridge (2009) implements the proxy-control-function in a single-step GMM framework, estimating input elasticities and the productivity process jointly rather than in two stages. Wooldridge's approach is widely used in firm-level applications and has been shown to perform better than the Levinsohn–Petrin and the Olley–Pakes estimators in firm-level applications (Van Beveren, 2012; Biesebroeck, 2007; Bournakis & Mallick, 2018).

For the baseline TFP estimates corresponding to equation (1), I construct value added as turnover minus material costs, while capital and labor inputs are measured by tangible fixed assets and total employee costs, respectively. In the Olley–Pakes (OP) estimator, investment measured as the change in tangible fixed assets plus depreciation is used as the proxy for productivity shocks, whereas material costs serve as the proxy in the Levinsohn–Petrin (LP), Ackerberg–Caves–Frazer (ACF), and Wooldridge (WRDG) estimators. All nominal variables are deflated using country–industry price indices from EU KLEMS and the OECD. As a further robustness check (Appendix D), I estimate TFP using turnover as output, employee costs as labor input, and capital stock measured by a perpetual-inventory-method (PIM).

3.2 Baseline Tests

My baseline regression equation is derived from the TFP catch-up framework proposed by Griffith et al. (2009)

$$\Delta lnTFP_{ijct} = \alpha_0 + \alpha_1 \Delta lnTFP_{Fjct} + \alpha_2 lnTFPGap_{ijct-} \ \ + \alpha_3 I_{ct}$$

$$+ \alpha_4 I_{ct} \times lnTFPGap_{ijct-} \ \alpha_5 I_{jt} + \alpha_6 lnTFPGap_{ijc} \quad \times I_{jt}$$
$$+\delta_{ct} X_{ct} + \delta_i + \delta_t + \varepsilon_{ijct} \qquad (2)$$

where the dependent variable $\Delta lnTFP_{ijct}$ denotes the TFP growth for firm *i* operating in industry *j*, country *c*, and year *t*. As discussed, I use the TFP measure from Wooldridge (2009) as benchmark, while alternative estimators are considered for robustness. The technological frontier F is defined within each country–industry–year cell as the 95th percentile of the firm-level TFP distribution. Using the 95th percentile mitigates measurement error caused by year-to-year fluctuations (Griffith et al., 2009; Gemmell et al., 2018). Nonetheless, I also verify robustness with stricter frontiers such as the top 1% and the highest-TFP firm in the cell, and with an EU-wide industry-year frontier (see Section 5.4). The coefficient α_1 reflects the spillover effect of frontier on firms lagging behind. Prior studies (Griffith et al., 2004; Cameron, 2005; Aghion et al., 2015) suggest that technological diffusion, enhanced knowledge, and best practices at the frontier are expected to positively affect a firm's productivity growth (α_1> 0).

The term $lnTFPGap_{ijct-1}$ ($= ln\frac{TFP_{Fjt-1}}{TFP_{ijt-1}}$) measures the firm's distance to the frontier in the prior period. Under this log-ratio definition, a value of 0 indicates the firm is at the frontier, and larger positive values indicate it is further behind. Accordingly, α_2 captures the speed of catch-up (Bernard & Jones, 1996; Cameron, 2005) by linking a firm's productivity growth to its distance from the frontier. Following Griffith et al. (2009), I expect larger gaps should imply greater potential for improvement, resulting in faster catch-up rates (α_2> 0).

Several papers (Arnold et al., 2011; Romero-Jordán et al., 2020; Gemmell et al., 2018) adapt this design to taxes by adding an interaction term of the productivity gap and the tax rate $lnTFPGap_{ijct-} \ \times CITR_{ct}$. I adjust this design by further accounting for the direct association of the corporate income tax rate $CITR_{ct}$ and productivity growth. Thus, my baseline model is

$$\Delta lnTFP_{ijct} = \alpha_0 + \alpha_1 \Delta lnTFP_{Fjct} + \alpha_2 lnTFPGap_{ijct-1} + \alpha_3 CITR_{ct}$$
$$+ \alpha_4 lnTFPGap_{ijct-} \ \times CITR_{ct} + \alpha_5 I_{jt} + \alpha_6 lnTFPGap_{ijc} \quad \times I_{jt}$$
$$+\delta_{ct} X_{ct} + \delta_i + \delta_t + \varepsilon_{ijct} \qquad (3)$$

I measure $CITR_{ct}$ as the statutory corporate income tax rate (for robustness tests see Section 5.4.). The tax coefficient α_3 captures the frontier's semi-elasticity of TFP growth with respect to the tax rate (H1), while α_4 represents how that semi-elasticity changes with distance to the frontier or the catch-up adjustment (H2). As predicted in H1 and H2, higher tax rates are associated with higher TFP growth at the frontier ($\alpha_3 > 0$ supporting H1) and a slower catch-up as firms move further from the frontier ($\alpha_4 < 0$ in line with H2 and prior studies e.g., Gemmell et al., 2018; Romero-Jordán et al., 2020). Note that the TFP measures in this paper rely on the financial-statement variables that are mechanically linked to firm-level effective tax rates. Thus, I generally use country-level tax rates to mitigate the endogenous tax-planning choices and simultaneity bias.

Following prior studies (e.g., Gemmel et al., 2018; Romero-Jordán et al., 2020), I include an interaction of TFP gap with sectoral profitability (I_{jt}) to capture industry-specific convergence trends. [1] Additional country-level controls X_{ct} comprise the ratios of government expenditure (*GE*) and government revenue (*GR*) to GDP, which proxy for fiscal environments that may affect TFP growth.

The baseline model also incorporates firm fixed effects δ_i to capture unobserved, time-invariant firm characteristics, and year-fixed effects δ_t to account for macroeconomic shocks, and the idiosyncratic error term ε_{ijct}. In alternative specifications, I replace firm-fixed effects with industry and country-fixed effects to verify the robustness. A closely related design is Gemmell et al. (2018), who estimate catch-up equations in EU countries with industry and country fixed effects and note that adding firm fixed effects alongside a lagged dependent variable would induce the Nickell (1981) downward bias. My focus, however, is on heterogeneous tax responses by distance to the frontier, for which a within-firm specification is preferable. Firm-fixed effects remove time-invariant traits correlated with *CITR* × *lnTFPGap*, sharpening identification of the interaction. Crucially, Equation (3) includes a lagged state variable (the lagged productivity gap $lnTFPGap_{t-a}$) rather than a lag of the dependent variable, so the classic Nickell bias does not apply. In addition, the observation period is reasonably large (T=15 years, see Section 4) further limits concerns about dynamic bias for short observation periods.

[1] To minimize concerns about the endogeneity of this variable and to capture the inherent profitability of an industry rather than any effect of CIT in a country on this variable, I follow Arnold et al. (2011) to use the industry profitability level for the U.S. as a proxy. Data source is derived from the U.S. Benchmark Input–Output Database. For each ISIC industry, a profitability ratio is calculated as gross operating surplus divided by value added, and it is then applied to the 2005–2019 period.

3.3 Heterogeneity Tests

To examine whether productivity responses vary across firm types, I analyze heterogeneity by firm size and ownership structure. As discussed in section 2.2, larger firms typically have better access to finance and stronger market positions compared to liquidity-constrained smaller firms. Meanwhile, multinational enterprises (MNEs) can reallocate activity across borders and engage in tax planning (e.g., profit shifting), potentially diluting the influence of statutory tax rates on productivity growth. Consequently, I anticipate the association between CITR and TFP growth to be less pronounced for larger and multinational firms. Moreover, large and multinational firms often act as technological leaders within their industries, generating positive spillovers that enhance the productivity of followers (Melitz, 2003; Javorcik, 2004; Mariotti, 2015; McGaughey et al., 2020). Their differential response to CITR compared to domestic and smaller firms are consistent with the prediction that the CITR-productivity relationship is moderated by firms' relative distance from the technological frontier.

For each heterogeneity dimension, I estimate two complementary specifications. Regarding firm size, I first re-estimate Equation (3) separately for three subsamples: large firms (≥ 250 employees) and small- and medium-sized enterprises (SMEs) (< 250 employees) and only small firms (<50 employees). Then, I extend the baseline model with an indicator *Large*, that represents large firms, and its interactions with the key regressors. I provide the related equation below:

$$\begin{aligned}\Delta lnTFP_{ijct} = \ & \alpha_0 + \alpha_1 \Delta lnTFP_{Fjct} + \alpha_2 lnTFPGap_{ijct-1} + \alpha_3 CITR_{ct} \\ & + \alpha_4 lnTFPGap_{ijct-} \times CITR_{ct} + \beta_1 Large_{ict} \\ & + \beta_2 lnTFPGap_{ijc} \times Large_{ict} + \beta_3 CITR_{ct} \times Large_{ict} \\ & + \beta_4 lnTFPGap_{ijct-} \times CITR_{ct} \times Large_{ict} + \delta_{ct} X_{ct} + \delta_j + \delta_c + \delta_t + \varepsilon_{ijct} \quad (4)\end{aligned}$$

Here, coefficients β_3 and β_4 indicate how the level and gap-dependent associations with CITR differ between large firms and SMEs. I expect β_3 to offset α_3 (opposite sign), and β_4 to offset α_4 (opposite sign), implying a weaker productivity response for large firms. Note that I employ industry δ_j and country fixed δ_c effects rather than firm δ_i fixed effects, as there is not much variation of firm size over time. Therefore, the heterogeneity tests with firm-specific interaction terms rely not on cross-sectional variation but on variation over time.

Similarly, I perform sub-sample tests for domestic firms (those without any subsidiary in other countries) and multinational enterprises (MNEs, those with at least one majority-owned subsidiary abroad). Following Eichfelder et al. (2025), I define a parent firm and its subsidiaries as domestic if the parent does not hold any stake in a firm that is settled abroad. Thus, firms are classified as MNE firms if either the parent or at least one of its majority-owned subsidiaries is located in another country than the other group members.

Then, I replace the *Large* dummy in Equation (4) with an *MNE* indicator variable (MNE=1 for multinational firms) to study ownership heterogeneity. The model specification is then:

$$\begin{aligned}\Delta lnTFP_{ijct} = {} & \alpha_0 + \alpha_1 \Delta lnTFP_{Fjct} + \alpha_2 lnTFPGap_{ijct-1} + \alpha_3 CITR_{ct} \\ & + \alpha_4 lnTFPGap_{ijct-} \times CITR_{ct} + \partial_1 MNE_{ict} \\ & + \partial_2 lnTFPGap_{ijct-1} \times MNE_{ict} + \beta_3 CITR_{ct} \times MNE_{ict} \\ & + \partial_4 lnTFPGap_{ijct-1} \times CITR_{ct} \times MNE_{ict} + \delta_{ct} X_{ct} + \delta_j + \delta_c + \delta_t + \varepsilon_{ijct} \quad (5)\end{aligned}$$

4. Data

4.1 Data and Sample

The sample comes from Bureau van Dijk's AMADEUS database, which provides unconsolidated firm-level financial statements and ownership information for European companies. Each observation corresponds to an individual entity, which may be a subsidiary within a corporate group. Compared to consolidated data, unconsolidated accounts are preferable for productivity estimation. While consolidated statements include group-level adjustments (e.g., intra-group eliminations, goodwill, purchase price allocations) that add noise to a production function, unconsolidated data reflect the productions at each operating entity. They also map cleanly to domestic tax regimes of each subsidiary, while consolidation blends jurisdictions and obscures policy exposure. By focusing on entity-level data, the empirical design minimizes potential endogeneity concerns related to reverse causality, as statutory tax rates are set at the country level, not by individual firms' performance. Additionally, the ownership information enables the classification of multinational-group affiliates vs. domestic firms, which is essential for the heterogeneity analysis.

I begin with EU-domiciled parent firms identified as global ultimate owners (GUO) in AMADEUS and their EU-28-domiciled subsidiaries, using unconsolidated statements. I exclude public administration, financial institutions, and insurance as these sectors face distinct tax and reporting regimes. Accordingly, I exclude the sectors of recycling (NACE 37), refuse disposal (NACE 38) and utilities (NACE 40, 41) due to their high share of public ownership in some countries over the sample period. In addition, financial services and holding companies (NACE 64–66) are excluded due to different reporting standards in these sectors. Finally, public administration (NACE 84), human health and social work (NACE 86–88), gambling (NACE 92), membership organizations (NACE 94) and households (97–98) are also excluded from the sample.

I retain only public and private limited companies, excluding legal forms typically outside the CIT base (e.g., sole proprietorships, partnerships). I drop observations with missing or implausible and negative values for turnover, materials, assets, investment, employees, and value added to ensure meaningful production accounts. As Equation (3) requires information on once-lagged TFP gaps, the final data set covers the period from 2006 to 2019.

The final data also incorporates supplementary information on corporate income tax rates from KPMG (for 2005-2013) and OECD (for 2014-2019) tax statistics. For effective marginal tax rates (EMTR) and effective average tax rates (EATR) I use information from Spengel et al. (2025). Country-level data, including government expenditure and revenue, are obtained from Eurostat, while price deflators from the EUKLEMS and OECD databases are used to calculate the real value of inputs and outputs. In addition, I follow Gemmel et al. (2018) and use information from the U.S. Bureau of Economic Analysis Database to calculate industrial profitability ratio for each industry. In doing so, I divide gross operating surplus by value added for each four-digit industry. Following prior studies (e.g., Gemmel et al., 2018; Arnold et al., 2011), I further restrict the analysis to firms below the productivity frontier.

Table 2 – Number of Observations by Year and Country

Country	Year														
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total
Austria	1	1	1	71	148	180	196	213	2	23	354	611	613	0	2,414
Belgium	1,092	1,153	1,118	1,076	1,152	1,299	1,320	1,303	1,060	3,830	3,551	3,324	3,236	3,165	27,679
Czech Republic	1,401	1,641	1,369	1,316	1,679	1,811	1,772	1,598	1,042	2,101	1,989	1,957	2,078	1,977	23,731
Estonia	163	197	185	108	99	149	172	186	213	430	441	448	466	0	3,257
Finland	884	1,070	929	803	873	991	1,074	1,107	704	1,414	1,276	1,307	1,415	0	13,847
France	3,460	3,362	2,895	2,312	2,445	2,511	1,684	1,756	1,603	7,642	7,264	7,052	6,551	6,120	56,657
Germany	615	1,030	1,210	1,267	1,458	1,754	1,835	1,636	582	1,782	1,823	1,875	2,038	2,205	21,110
Hungary	10	50	154	155	201	198	213	251	191	610	575	576	574	0	3,758
Italy	2,586	3,604	3,499	3,275	3,121	3,642	5,007	4,959	0	0	1	0	0	0	29,694
Luxembourg	0	0	4	10	16	18	13	16	13	9	0	0	0	0	99
Netherlands	6	11	4	0	0	0	0	0	0	0	0	0	0	0	21
Poland	667	847	835	968	895	656	337	186	65	186	171	1,032	2,390	0	9,235
Portugal	0	1,121	1,159	1,150	8	0	0	0	0	0	0	0	0	0	3,438
Slovenia	185	212	217	179	192	244	241	240	186	497	483	498	519	0	3,893
Slovakia	299	406	454	415	504	557	564	565	281	530	754	952	1,043	1,034	8,358
Spain	1,916	223	1	0	0	0	0	0	0	9,949	10,141	10,385	0	0	32,615
Sweden	1,488	1,787	1,840	1,841	2,080	2,236	2,222	2,172	1,553	9,367	9,404	9,519	9,602	9,493	64,604
Total	14,773	16,715	15,874	14,946	14,871	16,246	16,650	16,188	7,495	38,370	38,227	39,536	30,525	23,994	304,410

Table 2 reports the final sample of 304,410 firm–year observations from 2006-2019 across 18 European countries for the estimates. As this is not representative not administrative data, coverage reflects availability and reporting in commercial sources, leading to an unbalanced panel across countries and years. A few countries account for most observation: Sweden (roundly 65,000 observations) and France (roundly 57,000), followed by Spain and Italy. Critically, some countries are under-represented (e.g., Germany) while others are over-represented (e.g., Czech Republic) relative to their economic size. Thus, the baseline regressions in Section 3 use sampling (GDP) weights to mitigate the potential composition effects.

4.2 Descriptive Statistics

Table 3 provides descriptive statistics for the whole sample of 304,410 firm–year observations. [2] Firm size displays a strongly right-skewed distributions with means far exceeding medians for value added (mean $17.9 Million, median $4.1 Million), number of employees (mean 114, median 31) and total cost of employees (mean $5.8 Million, median $1.4 Million). Balance-sheet measures show the same pattern. Mean total assets and fixed assets are $39.1 Million and $19.6 Million (medians $ 6.9 Million and $ 1.3 Million), respectively, and average tangible fixed assets are $9.5 Million (median $ 0.7 Million) with large standard deviations (SD) confirming heavy upper tails. The average industrial profitability ratio is 0.371, suggesting that industries generate a profit equal to 37.1% of their value-added output on average. Approximately 46.7% of the firms are classified as multinational enterprises (MNEs), indicating a relatively balanced distribution between MNEs and domestic firms, while large firms make up only 9.2% of the total sample. Tax variables display plausible cross-country year variation. The statutory CITR averages 27.0%, whereas, the EATR (25.6%) and EMTR (19.96%) are lower, suggesting the presence of tax planning strategies among firms. The top personal income tax rate (PITR) averages 46.5%. Reported standard errors ranging from six to twelve percentage points indicate sufficient variation. At macro level, average GDP is $1.3 trillion with substantial dispersion across countries (standard deviation $1.8 trillion), while government revenue and expenditure average 47.2% and 49.2% of GDP, respectively, suggesting relatively stable fiscal shares (standard deviation in both cases 5.5.%).

[2] The descriptive statistics for each sub-sample are available in Table C3, Appendix C.

Table 3 – Descriptive Statistics of Firm Characteristics

Total sample	N	Mean	Median	SD
Value added ($100,000s)	304,410	178.885	40.723	1,134.445
Cost of employees ($100,000s)	304,410	58.188	14.419	302.844
Number of employees	304,410	114.396	31.000	515.325
Total assets ($100,000s)	304,410	391.881	64.926	6,527.375
Fixed assets ($100,000s)	304,410	196.672	13.865	4,736.316
Tangible fixed assets ($100,000s)	304,410	95.089	7.024	1,687.352
Industrial profitability ratio	304,410	0.371	0.351	0.142
Large firms	304,410	0.092	0	0.289
MNEs	297,078	0.467	0	0.499
Statutory corporate tax rate	304,410	27.013%	28.000%	5.689%
Personal income tax rate	304,410	46.475%	49.000%	12.126%
Effective average tax rate	304,410	25.596%	24.900%	6.497%
Effective marginal tax rate	304,410	19.959%	17.400%	9.055%
GDP ($1000,000,000s)	304,410	1,300.908	555.455	1,118.913
Government revenue (%)	304,410	47.261%	49.900%	5.470%
Government expense (%)	304,410	49.216%	50.200%	5.497%

This table presents descriptive statistics for observations in the main analysis. The variable 'value-added' represents the difference between turnover and material costs. The industrial profitability ratio for each industry is calculated as gross operating surplus divided by value added, derived from the U.S. Bureau of Economic Analysis Database. The statutory corporate income tax rates, including average local taxes and surtaxes, are taken from KPMG tax tables (2005-2013) and OECD corporate tax tables (2014-2019). The effective marginal tax rate (EMTR) and effective average tax rate (EATR) have been derived from Spengel et al. (2025). Government revenue and government expenditure are the ratio of total government revenue and government expenditure, respectively, to GDP.

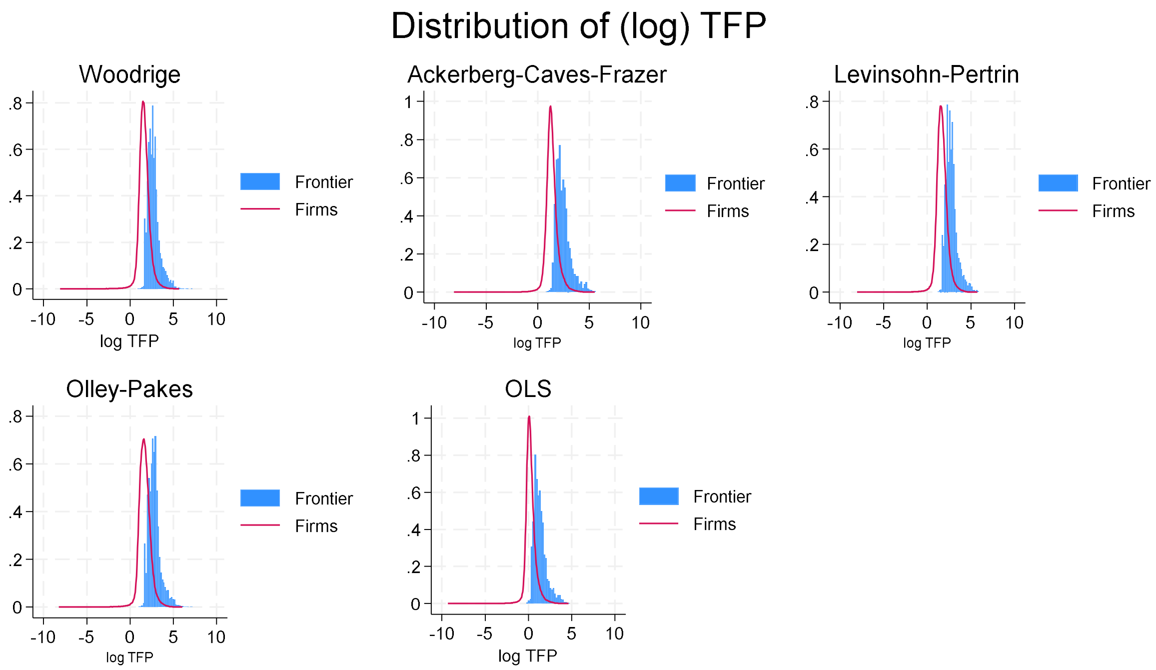
Table 4 summarizes frontier and non-frontier TFP for five alternative estimators. Minor differences in observation numbers reflect specific data requirements for each estimator. Average levels from the Wooldridge (2009) benchmark closely match those from Levinsohn–Petrin and Olley–Pakes, reflecting their shared assumptions (Van Beveren, 2012; Kané, 2022). The Ackerberg–Caves–Frazer estimator delivers slightly lower means, while naïve OLS yields markedly lower productivity levels. Importantly, the TFP gap between frontier and followers is remarkably similar across methods (≈1.05–1.08 in logs), indicating a stable productivity differential irrespective of estimator.

Table 4 – Descriptive Statistics of TFP Measures

	Mean (Std. Err)				
	WRDG	ACF	LP	OP	OLS
Non-frontiers' TFP estimates (log)	1.636 (0.613)	1.359 (0.583)	1.683 (0.622)	1.694 (0.646)	0.245 (0.577)
Frontiers' TFP estimates (log)	2.700 (0.683)	2.449 (0.693)	2.751 (0.675)	2.792 (0.702)	1.346 (0.750)
TFP gap of frontier to non-frontier (log)	1.046 (0.670)	1.066 (0.693)	1.052 (0.668)	1.081 (0.679)	1.078 (0.709)
Number of Observations	304,410	305,259	304,323	304,162	305,380

This table presents the statistics of TFP measured by using the equation $y_{it} = \alpha_0 + \beta l_{it} + \gamma k_{it} + \delta_{it} + \varepsilon_{it}$, at which y_{it} is the (log) value-added output, l_{it} is (log) cost of employees and k_{it} is (log) tangible fixed assets for firm i in year t, δ_{it} represents for TFP, and ε_{it} is white noise. WRDG, ACF, LP, OP, and OLS stand for the Wooldridge (2009), Ackerberg–Caves–Frazer (2015), Levinsohn–Petrin (2004), Olley–Pakes (1996), and Ordinary Least Squares estimator, respectively. The frontier is defined as firms that lie above the 95th percentile of the TFP distribution in each country–industry time period. The TFP gap is calculated based on the ratio of the TFP level of the frontier divided by the TFP level of each individual firm.

Figure 1 - Distribution of (log) TFP of Firms and Frontier



Source: Author's own Illustrations

Figure 1 reinforces this point by comparing the TFP distributions of frontier and non-frontier firms across estimators. The overall shapes of the distributions and the frontier–follower gaps are highly similar under WRDG, ACF, LP, and OP, whereas naïve OLS produces a noticeably tighter distribution. Taken together, the stability of these relative distributional patterns provides initial suggestion that the empirical analysis focused on log TFP and the TFP gap is not driven by a particular productivity measurement approach. This aligns with prior evidence that alternative estimators can shift productivity levels but generally preserve relative rankings and core relationships between productivity and other variables (Van Biesebroeck, 2007; Syverson, 2011; Ackerberg et al., 2015).

5. Empirical Findings

This section reports baseline estimates with the control variables and GDP-based sampling weights to address the cross-country over- and under-representation documented in Section 4. However, the results are qualitatively unchanged when the specifications are estimated without controls and when the regressions are re-estimated on the full unweighted sample (see Appendix D), indicating that the main findings are not driven by the controls or weighting scheme.

5.1 CITR and Productivity Growth

Table 5 reports the results for the baseline Equation (3). In column (1), I initially estimate the simple linear associations between *CITR* and productivity growth and do not find a significant average association of both variables. Once I allow for heterogeneous associations for firms with high and low productivity by including the interaction *lnTFPGap* × *CITR*, columns (2)–(6) provide consistent evidence to support H1 and H2 across all specifications. For H1, I observe higher productivity growth associated with tax rate increases, where the coefficients on CITR are positive and highly significant, ranging from 0.344 to 0.496. For H2, *lnTFPGap* × *CITR* is negative and significant, ranging from -0.186 to -0.399, indicating a slowdown with productivity catch up for firms moving further away from the frontier. Importantly, compared to the estimate in Gemmell et al. (2018), who use similar design on EU firms from 1996–2005, the coefficient on lnTFPGap × CITR in my preferred specification (≈ -0.36 in col. 3) matches both the sign and magnitude, even though I additionally include a direct CITR term. This indicates that recognizing the productivity response at frontier does not weaken the estimated catch-up response captured by the interaction.

Taken together, the evidence implies a nonlinear CITR–TFP relationship and explains why the simple linear model in column (1) does not display a clear association.

Table 5 – Baseline Results

Dependent variable: $\Delta\ln TFP_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln TFP_F$	0.229***	0.229***	0.230***	0.235***	0.101***	0.110***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)
lnTFPGap	0.401***	0.499***	0.530***	0.547***	0.176***	0.216***
	(0.008)	(0.019)	(0.021)	(0.024)	(0.011)	(0.013)
CITR	**-0.001**	**0.359*****	**0.409*****	**0.496*****	**0.433*****	**0.344*****
	(0.042)	**(0.074)**	**(0.075)**	**(0.083)**	**(0.045)**	**(0.051)**
lnTFPGap × CITR		**-0.348*****	**-0.360*****	**-0.399*****	**-0.186*****	**-0.249*****
		(0.064)	**(0.063)**	**(0.071)**	**(0.030)**	**(0.035)**
I_{jt}			-0.001	0.020	0.054**	-0.045*
			(0.043)	(0.047)	(0.023)	(0.026)
lnTFPGap × I_{jt}			-0.066**	-0.055	0.004	-0.007
			(0.032)	(0.035)	(0.016)	(0.017)
GE			0.283***	0.357***	0.239***	0.099
			(0.073)	(0.080)	(0.052)	(0.067)
GR			-0.851***	-0.832***	-0.425***	-0.004
			(0.090)	(0.100)	(0.071)	(0.065)
Observations	304,410	304,410	304,410	263,746	304,410	304,384
Number of Firms	79,842	79,842	79,842	69,907	79,842	79,823
R^2	0.228	0.229	0.230	0.236	0.096	0.111
Adjusted R^2	0.228	0.229	0.230	0.236	0.096	0.108
Firm FE	YES	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	NO	YES	NO
Industry FE	NO	NO	NO	NO	YES	NO
Industry-Country FE	NO	NO	NO	NO	NO	YES

This table presents the results of the baseline regression at which TFP is measured by the benchmark (WRDG) method. The dependent variable is the rate of productivity growth in firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year combination. The TFP gap is measured as the log ratio of TFP of the frontier *F* over TFP of firm *i* in industry *j*, country *c* in year *t*. I_{jt} is the industrial profitability, GE and GR stand for the total government expenditure and total government revenue, respectively. Appendix B provides detailed variable definitions. All regressions use the whole sample, except regression 4 that uses only observations from non-tax haven firms. Regressions 5 and 6 replace firm fixed effects by country and industry, and country–industry fixed effects, respectively. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and reported in parentheses.

The results are robust when excluding tax-haven observations (col. 4) and under alternative fixed-effects specifications (cols. 5–6). In addition, consistent with Gemmell et al. (2018), I find the larger absolute coefficient on the term *lnTFPGap × CITR* under firm fixed effects relative to industry and country fixed effects. This suggests that time-invariant firm heterogeneity might weaken the interaction in the boarder specifications.

Across all columns, the coefficients on $\Delta lnTFP_F$ (≈ 0.10–0.24) and on $lnTFPGap$ (≈ 0.18–0.55) are positive and significant, reinforcing the positive role of spillover and catch-up effects on the firm TFP growth (Griffith et al., 2009).

In terms of economic magnitude, Table 6 further reports the semi-elasticity of TFP growth with respect to the CITR at different points of the TFP-gap distribution using the baseline results in column (3). A 1-percentage-point increase in CITR is associated with a 0.41% increase in TFP growth for frontier firms (where the TFP gap equals 0) and with a 0.34% increase for near-frontier firms (p5). The productivity response then diminishes to 0.051% at median gap value and becomes increasingly negative, −0.106% at the 75th and −0.41% at the 95th percentile of the productivity gap.[3] Likewise, figure 2 visualizes this pattern. The relationship between CITR and TFP growth is positive for firms near to frontier, then weakening and turning negative as the productivity gap widens.

Table 6 –Average Associations of CITR and TFP Growth

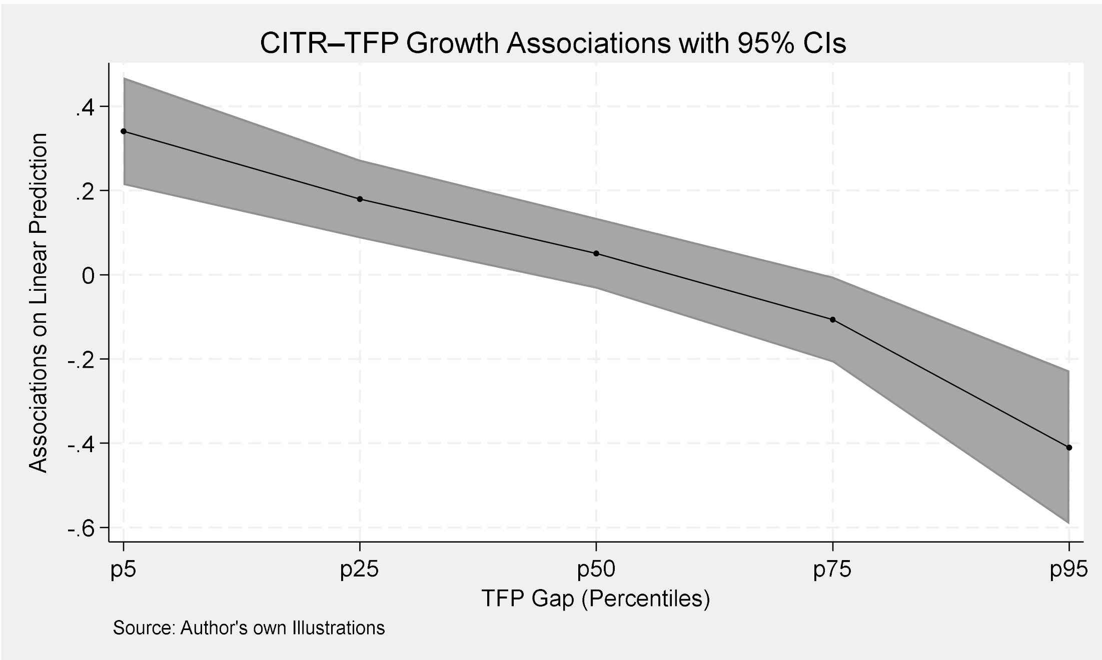
TFP Gap	$\frac{\partial(\Delta lnTFP)}{\partial(CITR)}$	**p-value**
5th Percentile (p5)	0.341***	0.000
25th Percentile (p25)	0.178***	0.000
50th Percentile (p50)	0.051	0.237
75th Percentile (p75)	-0.106**	0.040
95th Percentile (p95)	-0.410***	0.000

This table reports the average association (semi-elasticity) of the corporate income tax rate (CITR) and firm-level TFP growth, *∂(ΔlnTFP)/∂CITR*, evaluated at the 5th, 25th, 75th, and 95th percentiles of *lnTFPGap*. The average association is computed from the baseline specification (Table 5, col. 3), which includes the interaction lnTFPGap × CITR, so that $\frac{\partial(\Delta lnTFP)}{\partial CITR} = \widehat{\alpha}_{CITR} + \widehat{\alpha}_{lnTFP\ Gap\ \times CITR}\ ln\ TFP\ Gap.$ Reported p-values correspond to delta-method tests (from *margins, dydx(CITR)*) of the null hypothesis that the association at each percentile equals zero (H0: *∂(ΔlnTFP)/∂CITR* =0), using standard errors clustered at the firm level. Regressions are estimated with GDP weights.

[3] Considering the result in Model 3 Table 5, table 6 measures the semi-elasticity of TFP growth with respect to the CITR ($\hat{\beta}$) at different points of the TFP-gap distribution ($\Delta lnTFP = 0.235 - 0.223\ lnTFPGap$), holding all other independent variables at their means. The percentage change in TFP growth correlated to 1-percentage point change in CITR is calculated as $100[e^{(\hat{\beta})\times 0.01} - 1]$. For instance, using $\hat{\beta} = 0.341$ at the p5 of TFP gap, the percentage change in TFP growth is $100[e^{0.341\times 0.01} - 1] \approx +0.34\%$.

Together, these results indicate economically meaningful, strongly heterogeneous responses to CITR across the productivity distribution, consistent with H1 and H2. They align with Bournakis and Romero-Jordán (2024), who document heterogeneity in the innovation effects of the CITR across the TFP spectrum. In their study, lower-productivity firms face stronger innovation frictions when taxes rise, whereas high-productivity firms often see neutral or even positive impacts, especially on export performance. Taken together, the evidence reinforces that the CITR–productivity relationship is neither uniform nor linear, but varies systematically with a firm's distance from the technological frontier. Figure 2 illustrates this non-linear association of the CITR and TFP growth.

Figure 2 – Average Associations of CITR and TFP Growth



Source: Author's own illustration
Note: This figure plots the estimated average association, $\partial(\Delta lnTFP)/\partial CITR$, at the 5th, 25th, 75th, and 95th percentiles of *lnTFPGap*, computed from Table 5, col. 3 using *margins, dydx(CITR)*. Shaded area shows 95% confidence intervals based on the delta method with standard errors clustered at the firm level. Point estimates correspond to Table 6.

5.2 Baseline Results with Different TFP Measures

In Table 7, I replicate the baseline analysis using alternative TFP measures to assess the sensitivity of my results to the TFP estimation method. Columns (1)–(4) report estimates from my preferred specification (Table 5, col. 3) when TFP is measured using, respectively, the Ackerberg–Caves–Frazer (ACF) estimator (Ackerberg et al., 2015), the Levinsohn–Petrin (LP) estimator (Levinsohn and Petrin, 2003), the Olley–Pakes (OP) estimator (Olley and Pakes, 1996), and a naïve OLS approach. The sample size varies slightly across columns because each estimator imposes different data requirements. More importantly, across all four approaches, the coefficients on *CITR* and *lnTFPGap* × *CITR* remain consistent with the baseline obtained using the default Wooldridge (WRDG) estimator, indicating that alternative TFP measures do not affect the estimated productivity response to tax rates. The magnitudes are also similar, supporting the review by Syverson (2011) that the empirical results at plant- or firm-level studies are likely to be robust and little sensitive to TFP measurement choices. Taken together, the results in Tables 5 and 7 provide robust support for H1 and H2, confirming the nonlinear CITR–TFP growth relationship. Thus, it motivates further analysis of the mechanisms behind heterogeneous productivity effects across firms.

Table 7 – Baseline Results with Alternative TFP Measurement Techniques

Dependent variable: $\Delta lnTFP_i$	ACF (1)	LP (3)	OP (4)	OLS (5)
$\Delta lnTFP_F$	0.209***	0.234***	0.229***	0.191***
	(0.005)	(0.005)	(0.005)	(0.005)
lnTFPGap	0.495***	0.534***	0.539***	0.483***
	(0.020)	(0.022)	(0.022)	(0.019)
CITR	**0.460*****	**0.407*****	**0.358*****	**0.477*****
	(0.073)	**(0.076)**	**(0.077)**	**(0.072)**
lnTFPGap × CITR	**-0.347*****	**-0.359*****	**-0.370*****	**-0.362*****
	(0.059)	**(0.064)**	**(0.064)**	**(0.057)**
Observations	305,259	304,323	304,162	305,380
Number of Firms	79,739	79,861	79,842	79,696
R^2	0.210	0.234	0.230	0.194
Adjusted R^2	0.210	0.234	0.230	0.194
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

This table presents the results of sensitivity tests regarding different TFP measurement methodologies (col. 1: Ackerberg et al., (ACF); col. 2: Levinsohn–Petrin (LP) estimator; col. 3: Olley–Pakes (OP) estimator; and col. 4: OLS estimator. The dependent variable is the rate of productivity growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. All regressions include control variables, firm- and year-fixed effects. Controls include industry profitability interacted with TFP gap, total government expenditure, and total government revenues (ratio to GDP). *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

5.3 Heterogeneity Effects

5.3.1 Firm Size

Table 8 examines whether the non-linear association between CITR and TFP growth varies with firm size. As discussed, I expect that the association of CITR and productivity growth is stronger for smaller firms, which face tighter financial constraints, have fewer tax-avoidance opportunities, and are on average less productive. Columns (1)–(3) re-estimate the baseline model in Equation (3) separately for large firms (≥ 250 employees), SMEs (< 250 employees), and small firms (< 50 employees), respectively. The coefficients of *CITR* and *lnTFPGap* × *CITR* are insignificant for large firms, but statistically significant for SMEs and small firms, indicating a stronger response among smaller firms. Compared to prior firm-level studies using the Griffith et al. (2009) framework, Gemmel et al. (2018) and Romero-Jordán et al. (2020) also find the stronger catch-up effect for small firms and insignificant results for large firms. By contrast, Arnold and Schwellnus (2008) observe a weaker effect for small firms. However, they focus more on the interaction between tax rates and sectoral profitability and do neither account for the direct tax effect (CITR) nor for an interaction term of the CITR with the productivity gap.

Columns (4) and (5) estimate Equation (4), which interacts a *Large* indicator with the key regressors, first for the full sample and then excluding tax-haven jurisdictions. The pooled interaction model confirms the subsample results. The coefficients on *Large* × *CITR* are negative and significant at the 1% level, ranging from −0.411 to −0.359, implying a remarkably weaker productivity relationship with CITR for large firms. Moreover, *Large* × *lnTFPGap* × *CITR* is positive and statistically significant at the 1% level, showing that the negative gap-dependent slope observed for smaller firms attenuates among large firms. Quantitatively, the semi-elasticity of TFP growth with respect to CITR of large firms is smaller, about 0.485 – 0.359 ≈ 0.13 in Column (4), and the corresponding gap interaction is near zero (-0.221 + 0.277 ≈ 0.06). Excluding tax-haven firms sustains these patterns and slightly strengthens the magnitudes.

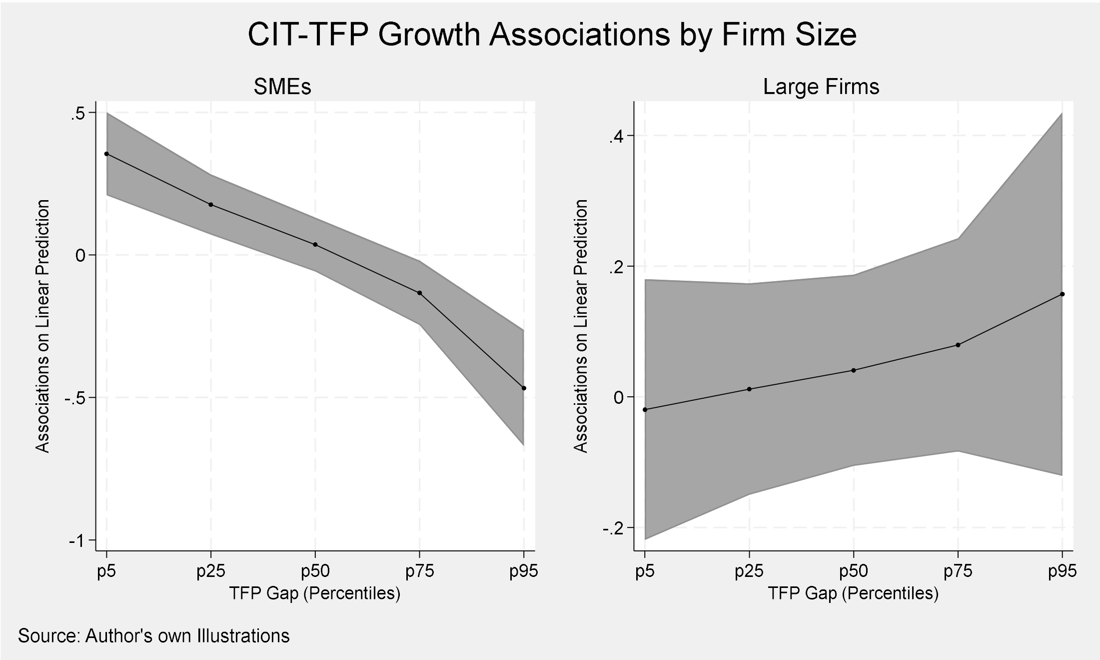
Table 8 – Heterogeneity by Firm Size

Dependent variable: $\Delta \ln TFP_i$	Large	SME	Small	Whole sample	Non-tax haven sample
	(1)	(2)	(3)	(4)	(5)
$\Delta \ln TFP_F$	0.118***	0.247***	0.298***	0.102***	0.100***
	(0.012)	(0.006)	(0.008)	(0.004)	(0.003)
lnTFPGap	0.191***	0.581***	0.689***	0.195***	0.203***
	(0.044)	(0.023)	(0.031)	(0.012)	(0.012)
CITR	**-0.028**	**0.501*** **	**0.820*** **	**0.485*** **	**0.566*** **
	(0.108)	**(0.087)**	**(0.135)**	**(0.049)**	**(0.053)**
lnTFPGap × CITR	**0.086**	**-0.411*** **	**-0.537*** **	**-0.221*** **	**-0.264*** **
	(0.100)	**(0.071)**	**(0.100)**	**(0.034)**	**(0.037)**
Large				0.174***	0.191***
				(0.016)	(0.018)
Large × lnTFPGap				-0.118***	-0.120***
				(0.015)	(0.017)
Large × CITR				**-0.359*** **	**-0.411*** **
				(0.054)	**(0.064)**
Large × lnTFPGap × CITR				**0.277*** **	**0.262*** **
				(0.055)	**(0.064)**
Observations	27,980	276,430	192,731	304,409	263,745
Number of Firms	6,298	73,544	53,921	79,841	69,906
R^2	0.149	0.245	0.287	0.099	0.100
Adjusted R^2	0.148	0.245	0.287	0.099	0.100
Firm FE	YES	YES	YES	NO	NO
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES

This table presents the results of heterogeneity tests regarding firm sizes. *Large* is a dummy variable for large firms at least 250 employees. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: large firms, SMEs (fewer than 250 employees), and small firms (fewer than 50 employees), respectively. Regressions 4 and 5 report the results of Equation (4) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable is the rate of productivity growth in firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Figure 3 complements Table 8 by plotting the average association between CITR and TFP growth across the TFP-gap distribution for SMEs (left) and large firms (right). For SMEs, the slope is positive near the frontier (p5–p25) but declines steadily, then turns negative and economically meaningful by p75–p95. The confidence intervals excluding zero over much of this range indicate the statistically significant association. In contrast, the productivity response of large firms is flat to mildly increasing and remains statistically indistinguishable from zero across percentiles. This pattern supports the findings by Fang et al. (2023) who use difference-in-differences analyses to identify the impact of CITR changes on TFP levels in China.

Figure 3 – Average Associations between CITR and TFP Growth by Firm Size



Source: Author's own illustration
Note: This figure plots the estimated average association, *∂(ΔlnTFP)/∂CITR*, at the 5th, 25th, 75th, and 95th percentiles of *lnTFPGap*, separately for SMEs and large firms. The underlying subsample regressions are reported in Table 8 (col. 1: large firms; col. 2: SMEs) and follow the baseline specification (firm and year fixed, GDP weights). Percentile-specific associations are obtained from post-estimation *margins, dydx(CITR)*. The shaded area shows 95% confidence intervals based on the delta method with standard errors clustered at the firm level.

5.3.2 Multinational Status

I now turn to heterogeneity by ownership structure. As discussed earlier, I expect a stronger CITR–TFP relationship for domestic firms that operate in a single national market. Similar to SMEs, these firms have on average more liquidity constraints, less avoidance opportunities and are less productive than their multinational competitors (Bernard & Jensen, 1999; Greenaway & Yu, 2004). Columns (1)–(3) of Table 9 re-estimate the baseline model in Equation (3) for MNEs, non-haven MNEs (i.e., MNEs without any subsidiary or shareholder in a tax-haven country), and domestic firms, respectively. For MNEs (cols. 1 and 2), the coefficients on *CITR* and *lnTFPGap* × *CITR* are close to zero and statistically insignificant. By contrast, for domestic firms (col. 3) the coefficient of *CITR* is positive and significant, while the coefficient of *lnTFPGap* × *CITR* is negative and significant, reinforcing the non-linear CITR–TFP relationship. Notably, both magnitudes estimated for domestic firms exceed the whole-sample estimates (Table 5, col. 3).

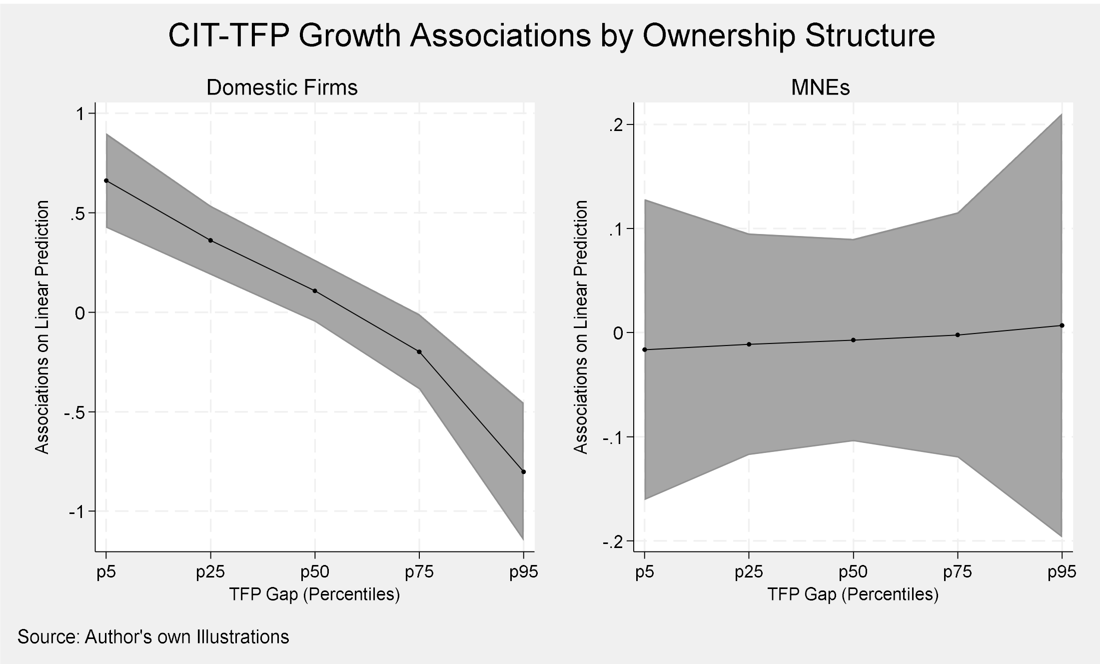
Table 9 – Heterogeneity by Multinational Status

Dependent variables: $\Delta \ln TFP_i$	MNE (1)	Non-haven MNE (2)	Domestic (3)	Full sample (4)	Non-haven sample (5)
$\Delta \ln TFP_F$	0.203***	0.207***	0.264***	0.104***	0.103***
	(0.007)	(0.008)	(0.008)	(0.004)	(0.003)
lnTFPGap	0.409***	0.433***	0.666***	0.238***	0.228***
	(0.027)	(0.032)	(0.035)	(0.015)	(0.015)
CITR	**-0.004**	**0.056**	**0.936*****	**0.734*****	**0.718*****
	(0.082)	**(0.096)**	**(0.146)**	**(0.065)**	**(0.068)**
lnTFPGap × CITR	**-0.001**	**-0.052**	**-0.691*****	**-0.354*****	**-0.335*****
	(0.075)	**(0.090)**	**(0.113)**	**(0.047)**	**(0.048)**
MNE				0.192***	0.163***
				(0.020)	(0.022)
MNE × lnTFPGap				-0.099***	-0.077***
				(0.017)	(0.019)
MNE × CITR				**-0.495*****	**-0.403*****
				(0.069)	**(0.076)**
MNE × lnTFPGap × CITR				**0.287*****	**0.215*****
				(0.059)	**(0.066)**
Observations	138,620	103,457	158,458	297,077	258,209
Number of Firms	33,678	25,532	43,956	77,633	68,266
R^2	0.217	0.226	0.253	0.100	0.102
Adjusted R^2	0.217	0.226	0.252	0.100	0.101
Firm FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Controls	YES	YES	YES	YES	YES

This table presents the results of heterogeneity tests regarding multinational ownerships. MNE is a dummy variable for multinational firms. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: MNEs, non-haven MNEs, and domestic firms, respectively. Regressions 4 and 5 report the results of Equation (5) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable is the log of TFP growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier F over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Figure 4 visualizes the relationships between CITR and TFP growth across the TFP-gap distribution for domestic firms (left) and MNEs (right). For domestic firms, the figure shows that the average association is positive near the frontier but declines steadily as the TFP gap widens, turning negative at higher percentiles. For MNEs, the estimated association is flat and statistically indistinguishable from zero across the distribution. Overall, Table 9 and Figure 4 provide consistent evidence that the nonlinear CITR–TFP relationship is more pronounced among domestic firms, while MNEs exhibit muted sensitivity consistent with the ability to leverage international operations and optimize tax positions.

Figure 4 – Average Associations of CITR and TFP Growth by Multinational Status



Source: Author's own illustration
Note: This figure plots the estimated average association, *∂(ΔlnTFP)/∂CITR*, at the 5th, 25th, 75th, and 95th percentiles of *lnTFPGap*, separately for MNEs and domestic firms. The underlying subsample regressions are reported in Table 9 (col. 1: MNEs; col. 3: Domestic firms) and follow the baseline specification (firm and year fixed, GDP weights). Percentile-specific associations are obtained from post-estimation *margins, dydx(CITR)*. The shaded area shows 95% confidence intervals based on the delta method with standard errors clustered at the firm level.

5.4 Robustness tests

In the final section, I conduct additional robustness tests to validate the robustness of my core findings by assessing alternative tax measures and different technological frontier specifications.

The baseline results presented in Table 5 rely on the statutory corporate income tax rate, which can overlook structural aspects of the tax system, such as depreciation rules, investment allowances, and interest deductibility (Vartia, 2008; Romero-Jordán et al., 2020). Moreover, it does not account for potential effects of the personal income tax rate (PITR) on firm outcomes (Mertens & Ravn, 2013). Higher PITR can reduce disposable income of owners and high-earning employees, discouraging investment and making it more challenging to attract and retain skilled talents. Additionally, higher PITR incentivize firms to reallocate effort toward tax planning, thereby diverting productivity-enhancing investments. To address these concerns, I (i) include the top PITR and its interaction with the TFP gap, and (ii) replace statutory CITR with the country-level effective average tax rate EATR.[4]

Table 10 reports results with whole sample (cols. 1, 3, and 5) and for firms located in non-tax haven jurisdictions (cols. 2, 4, 6). In columns (1) and (2), the positive coefficient on *CITR* and the negative interaction term *lnTFPGap* × *CITR* remain highly significant, implying that adding *PITR* does not affect the non-linear relationship between CITR and TFP growth. However, the magnitude of both CITR and *lnTFPGap* × *CITR* increase noticeably once PITR is included (compared to Table 5, col.3), indicating that PITR capture a correlated component of the tax environment relevant for productivity growth. Consistent with this interpretation, in columns (3) and (4), when I replace the statutory rate EATR and omit PITR, neither EATR nor its interaction with the TFP gap is statistically significant. By contrast, once PITR is controlled for in columns (5) and (6), the EATR specification closely mirrors the baseline non-linearity. *EATR* enters significantly positive (0.275 to 0.395) and *lnTFPGap* × *EATR* becomes significantly negative (–0.283 to –0.246), consistent with H1 and H2. This comparison suggests that the non-linear CITR-TFP growth is robust, but for effective tax measures, it is more cleanly recovered after separating corporate taxation from the

[4] I prefer using the EATR rather than the EMTR because EATR reflects the effective tax burden on profitable investments and is closer in interpretation to the statutory CIT rate. Moreover, TFP growth is more likely to reflect broad upgrading and technology adoption undertaken by profitable firms than the incentive for a single break-even marginal project. EMTR focuses on that marginal wedge and is highly sensitive to base provisions (e.g., depreciation rules), making it more closely tied to marginal investment than to productivity growth.

personal-tax channel. Finally, PITR enters negatively with a positive interaction with the TFP gap, reinforcing the view that corporate and personal taxes operate through distinct channels.

Table 10 – Robustness Test with Alternative Tax Measures

Dependent variable: $\Delta \ln TFP_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln TFP_F$	0.230***	0.235***	0.230***	0.235***	0.230***	0.236***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
lnTFPGap	0.447***	0.464***	0.419***	0.436***	0.356***	0.373***
	(0.022)	(0.025)	(0.020)	(0.022)	(0.021)	(0.024)
CITR	**0.893*****	**0.969*****				
	(0.080)	**(0.088)**				
lnTFPGap x CITR	**-0.804*****	**-0.827*****				
	(0.071)	**(0.079)**				
EATR			**-0.012**	**0.110**	**0.275*****	**0.395*****
			(0.067)	**(0.075)**	**(0.072)**	**(0.080)**
lnTFPGap x EATR			**0.025**	**-0.018**	**-0.246*****	**-0.283*****
			(0.060)	**(0.069)**	**(0.066)**	**(0.075)**
PITR	-0.193***	-0.171***			-0.029	-0.015
	(0.053)	(0.060)			(0.052)	(0.059)
lnTFPGap x PITR	0.488***	0.478***			0.313***	0.309***
	(0.041)	(0.045)			(0.040)	(0.044)
Observations	304,410	263,746	304,410	263,746	304,410	263,746
Number of Firms	79,842	69,907	79,842	69,907	79,842	69,907
R^2	0.234	0.240	0.393	0.275	0.393	0.275
Adjusted R^2	0.234	0.240	0.218	0.274	0.218	0.274
Controls	YES	YES	YES	YES	YES	YES

This table reports additional regression results using alternative tax measures. Regressions (1) and (2) use the statutory corporate income tax rate, consistent with the baseline model, while regressions (3)–(6) use the effective average tax rate (EATR). All egressions also control for industry profitability interacted with the TFP gap, total government expenditure, and government revenue (as a share of GDP). The analysis is based on the full sample (Regressions 1,3, 5) and non-tax haven sample (Regressions 2, 4, 6), and includes firm and year fixed effects. The dependent variable is the log of TFP growth for firm *i* in year *t*. The productivity frontier *F* is defined as the 95th percentile of the TFP distribution within each country–industry–year cell. The TFP gap is measured as the log ratio of TFP at the frontier to the TFP of each individual firm. Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

As a further robustness check, I alter the definition of the technological frontier and re-estimate the baseline analysis with the corresponding frontiers' TFP growth and TFP gap. I report these results in Table 11 for the full sample (cols. 1, 3, 5) and non-tax haven sample (cols. 2, 4, and 6). First, in column (1) and (2), I define an alternative frontier by using the highest-TFP firm in each country-industry-year. Columns (3) and (4) use the 99th percentile within each cell for the reference frontier. The results presented so far based on the frontiers defined by each country-industry-year pair. Instead, to account for technological spillovers and economic integration within the EU single market, columns (5) and (6) redefine the frontier as the industry–year 95th percentile across the whole sample. Note that sample size increases (e.g., 317,766 vs. 304,410 in the baseline) because the higher benchmarks convert some previously frontier firms into non-frontier observations that are usable in the baseline specification. Across all definitions, the nonlinear CITR–TFP relationship remains to support H1–H2. The level term on *CITR* is positive and significant, while *lnTFPGap* × *CITR* is negative and significant. Importantly, the magnitude of the positive *CITR* also is markedly larger than those observed in the baseline result (Table 5, col. 3). The results remain consistent even after excluding observations of firms with subsidiaries in tax-haven jurisdictions.

Table 11 – Robustness Test with Alternative Frontiers

Dependent variables: ΔlnTFP_i	Highest TFP level		99th Percentile		95th Percentile (EU Single Market)	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔlnTFP_F	0.046***	0.047***	0.092***	0.095***	0.306***	0.313***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.007)	(0.008)
lnTFPGap	0.207***	0.220***	0.303***	0.323***	0.762***	0.770***
	(0.008)	(0.009)	(0.011)	(0.013)	(0.025)	(0.027)
CITR	**1.178*** **	**1.286*** **	**1.102*** **	**1.224*** **	**0.930*** **	**1.025*** **
	(0.059)	**(0.064)**	**(0.066)**	**(0.073)**	**(0.081)**	**(0.090)**
lnTFPGap x CITR	**-0.433*** **	**-0.468*** **	**-0.475*** **	**-0.521*** **	**-0.673*** **	**-0.687*** **
	(0.022)	**(0.024)**	**(0.033)**	**(0.038)**	**(0.072)**	**(0.080)**
Observations	317,766	273,720	316,202	272,617	309,208	267,379
Number of Firms	81,829	71,385	81,586	71,221	80,343	70,247
R^2	0.066	0.068	0.102	0.107	0.327	0.333
Adjusted R^2	0.066	0.068	0.102	0.107	0.327	0.333
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

This table presents robustness checks using alternative definitions of the productivity frontier. Regressions (1) and (2) define the frontier as the maximum TFP level within each country–industry–year cell. Regressions (3) and (4) use the 99th percentile, while (5) and (6) use the 95th percentile of the TFP distribution within each industry-year cell (regardless of country). All regressions include controls for industry profitability interacted with the TFP gap, total government expenditure, and government revenue (as a share of GDP), along with firm and year fixed effects. Regressions (1), (3), and (5) use the full sample, while (2), (4), and (6) are restricted to firms in non–tax haven jurisdictions. The dependent variable is the log of TFP growth for firm i in year t. The TFP gap is defined as the log ratio of the TFP level at the respective frontier to the TFP of each individual firm. Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6. Conclusion

This study investigates the relationship between CITR and TFP growth. Using firm-panel data from EU countries between 2005–2019, my identification relies on the cross-country variation in business tax rates and TFP growth at firm level measured with Wooldridge's estimator. The empirical design follows a Griffith et al. (2009) catch-up framework to distinguish responses of the more and less productive firms. The results reveal a non-linear CITR–TFP relationship that varies across a firm's TFP level. Higher CITR are positively associated with TFP growth for the more productive firms, but negatively associated for the less productive firms. Heterogeneity analyses show that these patterns are markedly stronger for domestic firms and SMEs, whereas large firms and MNEs exhibit no statistically significant associations between the CITR and productivity growth. The findings remain robust to extensive sensitivity tests, (a) controlling for alternative fixed effects, (b) using alternative TFP measures, (c) excluding tax-haven observations, (d) controlling for personal income taxes, and (e) redefining the technological frontiers.

The study offers compelling implications for both academic research and policy. The results challenge the conventional assumption regarding a linear association between corporate taxation and productivity growth. Instead, I find evidence for a non-linear association between the CITR and productivity growth that is systematically moderated by the distance to the technological frontier. For research, accounting for this non-linearity can reconcile mixed evidence on average tax effects and opens avenues to study the mechanisms behind this non-linear relationship. From a policy perspective, the results highlight a trade-off between improving aggregated productivity level and reducing gaps. While higher CITRs may be growth-enhancing for more productive firms, they disproportionately hinder the productivity catch-up among smaller and less-productive firms. Thus, rather than the uniform tax rates, policymakers should consider targeted designs that balance redistributive and growth-enhancing objectives, especially to promote domestic firms and SMEs

I also acknowledge the limitations in my analysis particularly relevant to dataset. First, the TFP measures are based solely on firms' financial statements, which limits my ability to observe tax avoidance and profit-shifting behaviors at firm level. Nevertheless, using firms with subsidiaries in tax haven countries as proxy for avoidance opportunity, I still obtain robust results. Although the results are robust to alternative tax measures, linking the firm panel to administrative tax records or transaction-level data would permit direct assessments of how such strategies mediate the tax–

productivity relationship. Second, the data lacks detailed information on production inputs the composition of the labor force (e.g., white-collar workers versus blue-collar workers), and firm exits. Incorporating these elements would enhance the productivity estimates and help explore the mechanisms underlying the non-linear CITR–TFP relationship. These extensions are beyond the scope of the data but are interesting pathways for future work.

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Appendix A: TFP Measures and Estimation

Several methods for measuring firm productivity have been developed in the literature, each with distinct strengths and limitations. The classical Solow residual (Solow, 1957) calculates productivity as the part of output that cannot be explained by changes in capital and labor inputs, often interpreted as a measure of total factor productivity (TFP). While straightforward and intuitive, this method is susceptible to simultaneity bias (Klette & Griliches, 1996), asinput choices are influenced by unobserved productivity shocks.

Aigner et al. (1977) introduced stochastic frontier analysis (SFA), which decomposes productivity deviations into inefficiencies and random shocks. While this method allows for direct computation of the productivity gap, it relies on strong parametric assumptions about the production frontier and the distribution of inefficiency terms, which may not be appropriate across different industries. Furthermore, SFA does not fully address the endogeneity bias inherent in input choices.

In contrast, the Malmquist Productivity Index, based on Data Envelopment Analysis (DEA), is a non-parametric method that constructs a frontier and measures firms' relative efficiency using observed data. Unlike parametric methods, DEA does not impose a functional form between inputs and outputs, thus it does not control for input simultaneity. Additionally, DEA-based methods are sensitive to outliers, as extreme values can distort the efficiency frontier and lead to misleading productivity estimates (Simar & Wilson, 1998).

This study aims to analyze the relationship between corporate tax liabilities and firm productivity growth, which requires understanding how firms adjust their production decisions in response to changes in business tax rates. Thus, a productivity measure that accounts for firm-level heterogeneity and input simultaneity bias is more suitable for this analysis.

Building on the Cobb-Douglas production function, the relationship between output and inputs can be specified as follows:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \gamma_k k_{it} + \omega_{it} + \varepsilon_{it}, \qquad (1)$$

In this equation, y_{it} represents the logarithm of output, l_{it} denotes the logarithm of labor input, and k_{it} indicates logarithm of the capital stock for each firm i in year t. The variable ω_{it} that captures the residual after accounting for all input contributions reflect total factor productivity (TFP). The term ε_{it} is included as white noise to control idiosyncratic error.

As noted, a major challenge arises from the unobserved nature of productivity (ω_{it}), which may be correlated with input variables, leading to simultaneity bias in standard approaches (Gatto et al., 2011). This occurs because firms may adjust their input choices, such as labor and capital, based on their productivity expectations, resulting in biased estimates of TFP. Traditional methods for addressing endogeneity, including fixed-effects models or instrumental variable estimators, have proven inadequate in this context (Griliches & Mairesse, 1999).[5]

Olley and Pakes (1996, OP) propose one of the earliest proxy-control-function approaches to address simultaneity between input choices and unobserved productivity. Their method involves a two-stage estimation process, using investment as a proxy for unobserved productivity shocks. The key assumption is that, conditional on capital k_{it}, a firm's investment i_{it} is strictly increasing in productivity ω_{it}, so the investment policy function can be inverted:

$$i_{it} = f(\omega_{it}, k_{it}) \Rightarrow \omega_{it} = h(i_{it}, k_{it}) \tag{A1}$$

Substituting this control function into the production function (1) yields the first-stage regression:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \Phi(i_{it}, k_{it}) + \varepsilon_{it} \tag{A2}$$

$$\phi(i_{it}, k_{it}) \equiv \gamma_k k_{it} + h(i_{it}, k_{it}),$$

Where $\phi(.)$ is approximated flexibly (e.g., by a high-order polynomial). This stage identifies γ_l while controlling for productivity via $\Phi(i_{it}, k_{it})$. In the second stage, OP identifies γ_k by exploiting a law of motion for productivity:

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it} \tag{A3}$$

together with the orthogonality condition that innovations ξ_{it} are unanticipated and thus uncorrelated with predetermined capital (and selection is handled via a survival/exit equation). Intuitively, the first stage controls for productivity using investment, and the second stage uses productivity dynamics to identify the capital coefficient (γ_k) and productivity.

Levinsohn and Petrin (2004, LP) later modify the Olley-Pakes approach by replacing investment with an intermediate input (typically materials) as the proxy for the unobserved

[5] The fixed-effects estimator may deal with the labor-productivity correlation, but at the cost of imposing productivity shocks with no time variation. IV estimators are constrained by the difficulty of finding appropriate instruments.

productivity shock. Materials are adjusted more frequently in response to productivity changes and thus more reliable in cases where investment is either infrequent or shows many zero values (Petrin et al., 2024). Formally, let m_{it} denote (log) intermediate inputs, the intermediate-input demand function can be written and inverted as

$$m_{it} = f(\omega_{it}, k_{it}) \Rightarrow \omega_{it} = h(m_{it}, k_{it}) \quad \text{(A4)}$$

Similarly, substituting this control function into the production function yields the first-stage equation and identifies γ_l. In second sate, LP approach also γ_k and ω_{it} through a law of motion for productivity. Despite these improvements, both the OP and LP methods treat labor as a non-dynamic input, potentially biasing labor coefficient estimates.

Ackerberg et al. (2015) introduce a more flexible estimator (ACF) that allows for dynamic labor decisions, separating them from capital and material decisions. Start from a (gross-output) production function with intermediates:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \gamma_k k_{it} + \gamma_m m_{it} + \omega_{it} + \varepsilon_{it}, \quad \text{(A5)}$$

As in LP, ACF uses an intermediate input (e.g., materials) as the proxy. Under a monotonicity condition, the intermediate-input demand can be written as

$$m_{it} = f(\omega_{it}, k_{it}, l_{it}) \Rightarrow \omega_{it} = h_t(m_{it}, k_{it}, l_{it}) \quad \text{(A6)}$$

Substituting this control function into the production function yields the first-stage control-function:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \gamma_k k_{it} + \gamma_m m_{it} + h_t(m_{it}, k_{it}, l_{it}) + \varepsilon_{it} \equiv \Phi_t(m_{it}, k_{it}, l_{it}) + \varepsilon_{it} \quad \text{(A7)}$$

where $\Phi_t(.)$ is approximated flexibly. The input coefficients (especially γ_l) are not identified in the first stage because labor choice may respond to ω_{it}. Identification is thus achieved in the second stage by imposing a productivity law of motion: $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$, and using moment conditions with predetermined inputs (e.g., k_{it}) and suitable instruments (often lagged inputs) to identify γ_l, γ_k. Intuitively, ACF is designed to better accommodate settings where firms adjust labor dynamically in response to expected productivity. However, this approach may underperform when using gross output rather than value-added output, as it does not fully account for the role of intermediate inputs in the production process.

Wooldridge (2009, WRDG) proposes a one-stage method that addresses issues with the contemporaneous error correlation across equations and serial correlation within the two-stage procedures. This approach also exploit a law of motion for productivity $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$ and use a proxy variable (typically intermediate inputs m_{it} as in LP) to produce the control function $\omega_{it} = h_t(m_{it}, k_{it})$. However, Wooldridge's key step is to combine the control-function representation and the productivity law of motion into a single estimating equation:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \gamma_k k_{it} + g(h_{t-1}(m_{it-1}, k_{it-1})) + \xi_{it} + \varepsilon_{it} \tag{A8}$$

where $g(\cdot)$ and $h(\cdot)$ are approximated flexibly (e.g., polynomials). The parameters (γ_l, γ_k) are then estimated jointly by GMM using moment conditions of the form $\mathbb{E}[(\xi_{it} + \varepsilon_{it})Z_{it}] = 0$, with instruments Z_{it} taken from predetermined variables (e.g., k_{it} and typically lagged inputs l_{it-1} and m_{it-1}), reflecting that current productivity innovations are orthogonal to past choices. Thus, this approach allows for the simultaneous estimation of input coefficients and endogenous productivity response. While several studies, including those by Van Beveren (2012), Biesebroeck (2007), and Bournakis and Mallick (2018), have demonstrated that this approach is superior to the earlier OP and LP methods, WRDG still relies on the predetermined labor assumption.

Each method has distinct strengths and weaknesses in addressing the unobserved productivity shocks and simultaneity bias. This paper adopts the WRDG estimator as the benchmark for its flexibility with labor input, and compares results with the ACF, LP, OP, and naïve Ordinary Least Squares (OLS) estimators. Despite this preference, the relative distribution of productivity should remain consistent across different methodologies. Research by Van Biesebroeck (2007), Syverson (2011), and Ackerberg et al. (2015) indicates that while absolute productivity estimates may vary depending on the chosen approach (e.g., index numbers, parametric versus non-parametric methods, or value-added versus gross output specifications), the relative productivity patterns and key empirical findings between productivity and other variables tend to remain robust.

Appendix B: Variable Description

Variable	Definition	Data Source
Productivity Variables		
$\Delta lnTFP_{ijct}$	The growth of TFP for firm *i* of industry *j*, in country *c*, in year *t* calculated by the change in natural logarithmic difference of TFP for given firm i $(lnTFP_{ijct} - lnTFP_{ijct-1})$, at which TFP is the total factor productivity level estimated by WRDG estimator on the Cobb-Douglas value-added production function $y_{it} = \alpha_0 + \beta l_{it} + \gamma k_{it} + \delta_{it} + \varepsilon_{it}$. y_{it} is the log real value-added output, l_{it} is log real cost of employees and k_{it} is log of real tangible fixed assets.	Amadeus, EUKLEMS &OECD
$\Delta lnTFP_{Fjct}$	The change in the natural logarithm of TFP at the technological frontier *F* of industry *j*, in country *c*, at time *t* calculated by the logarithmic difference $(lnTFP_{Fjct} - lnTF_{Fjct-1})$, at which the productivity frontier in each country-industry-year is approximated by the productivity of firms that lie at the 95th percentile of the TFP distribution.	Amadeus, EUKLEMS &OECD
$lnTFPGap_{ijct-1}$	Lagged natural logarithm of the TFP gap between firm *i* and the technological frontier F in year t calculated as the ratio of the level of TFP of the relevant country-industry frontier to the TFP level of each firm at time *t-1* or $\frac{TFP_{Fjct-1}}{TFP_{ijt}-1}$.	Amadeus, EUKLEMS &OECD
Tax Variables		
$CITR_{ct}$	The statutory corporate income tax rate of country *c,* at time t	OECD
$EMTR_{ct}$	The effective marginal tax rate of country *c,* at time *t*	Mannheim Tax Index
$EATR_{ct}$	The effective average tax rate of country *c,* at time *t*	Mannheim Tax Index
$PITR_{ct}$	The top personal income tax rate of country *c,* at time *t*	OECD
Firm Indicators		
MNE_{ict}	Dummy variable that defines the ownership of firm *i* (1= multi-enterprise, 0= domestic firms).	Amadeus
$Large_{ict}$	Dummy variable that defines the size of firm i (1= Large firms with at least 250 employees, 0 = small and medium firms with fewer 250 employees)	Amadeus
Control Variables		
I_{jt}	Profitability ratio of industry j at time t in the U.S. calculated as gross operating surplus divided by value added, and then applied to the 2006–2019 period.	Bureau of Economic Analysis
GR_{ct},	Ratio of country *c*'s government revenue to its GDP	Eurostat
GE_{ct},	Ratio of country *c*'s government expenditure to its GDP	Eurostat

Appendix C: Additional Descriptive Statistics

This section reports the information for the tax-haven jurisdictions (Table C1), statutory tax rate (Table C2) and the descriptive statistics for the subsample of SMEs, larger firms, as well as domestic firms and MNEs (Table C3).

Table C1 – Tax-haven and non-cooperative jurisdictions

Source	**Year**	**Countries**
OECD	2009	Backlist: Costa Rica, Malaysia (Labuan), the Philippines, and Uruguay. Grey list: Andorra, Anguilla, Antigua and Barbuda, Aruba, Bahamas, Bahrain, Belize, Bermuda, British Virgin Islands, Cayman Islands, Cook Islands, Dominica, Gibraltar, Grenada, Liberia, Liechtenstein, Marshall Islands, Monaco, Montserrat, Nauru, Netherlands, Antilles, Niue, Panama, St Kitts and Nevis, St Lucia, St Vincent & Grenadines, Samoa, San Marino, Turks and Caicos Islands, Vanuatu.
Council of the European Union	2019	American Samoa, Belize, Fiji, Guam, Oman, Samoa, Trinidad and Tobago, US Virgin Islands, Vanuatu.

Table C2 – Statutory Corporate Income Tax Rate

Country	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Austria	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%	25%
Belgium	34%	34%	34%	34%	34%	34%	34%	34%	34%	34%	34%	34%	34%	30%	30%
Czech Republic	26%	24%	24%	21%	20%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%
Denmark	28%	28%	25%	25%	25%	25%	25%	25%	25%	25%	24%	22%	22%	22%	22%
Estonia	24%	23%	22%	21%	21%	21%	21%	21%	21%	21%	20%	20%	20%	20%	20%
Finland	26%	26%	26%	26%	26%	26%	26%	25%	25%	20%	20%	20%	20%	20%	20%
France	35%	34%	34%	34%	34%	34%	36%	36%	38%	38%	38%	34%	44%	34%	34%
Germany	38%	38%	38%	29%	29%	29%	30%	30%	30%	30%	30%	30%	30%	30%	30%
Hungary	16%	17%	20%	20%	20%	19%	19%	19%	19%	19%	19%	19%	9%	9%	9%
Italy	37%	37%	37%	31%	31%	31%	31%	31%	31%	31%	31%	31%	28%	28%	28%
Luxembourg	30%	30%	30%	30%	29%	29%	29%	29%	29%	29%	29%	29%	27%	26%	25%
Netherlands	32%	30%	26%	26%	26%	26%	25%	25%	25%	25%	25%	25%	25%	25%	25%
Poland	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%	19%
Portugal	28%	28%	27%	27%	27%	27%	29%	32%	32%	32%	30%	30%	30%	32%	32%
Slovakia	19%	19%	19%	19%	19%	19%	19%	19%	23%	22%	22%	22%	21%	21%	21%
Slovenia	25%	25%	23%	22%	21%	20%	20%	18%	17%	17%	17%	17%	19%	19%	19%
Spain	35%	35%	33%	30%	30%	30%	30%	30%	30%	30%	28%	25%	25%	25%	25%
Sweden	28%	28%	28%	28%	26%	26%	26%	26%	22%	22%	22%	22%	22%	22%	21%

Table C3 – Descriptive Statistics of Firm Characteristics in Sub-Sample

Large Firms

Variables	**Obs.**	**Mean**	**Median**	**SD**
Value added ($100,000s)	27,980	1,188.998	573.608	3,562.851
Cost of employees ($100,000s)	27,980	390.947	219.895	929.661
Number of employees	27,980	775.959	433.000	1,541.686
Total assets ($100,000s)	27,980	2,721.892	768.983	21,228.438
Fixed assets ($100,000s)	27,980	1,512.075	240.321	15,425.158
Tangible fixed assets ($100,000s)	27,980	702.814	148.243	5,492.278
Industrial profitability	27,980	0.374	0.357	0.129
MNEs	26,776	0.812	1.000	0.390
Statutorty corporate tax rate	27,980	0.274	0.295	0.061
Personal income tax rate	27,980	0.427	0.475	0.132
Effective average tax rate	27,980	0.264	0.282	0.067
Effective marginal tax rate	27,980	0.210	0.218	0.087
GDP ($1000,000,000s)	27,980	1,723.625	1,312.539	1,385.818
Government revenue (%)	27,980	0.460	0.455	0.053
Government expense (%)	27,980	0.479	0.452	0.058

SMEs

Variables	**Obs**	**Mean**	**Median**	**SD**
Value added ($100,000s)	276,430	76.642	34.237	136.659
Cost of employees ($100,000s)	276,430	24.506	12.231	34.315
Number of employees	276,430	47.433	26.000	55.547
Total assets ($100,000s)	276,430	156.039	54.472	837.565
Fixed assets ($100,000s)	276,430	63.528	11.153	653.915
Tangible fixed assets ($100,000s)	276,430	33.575	5.494	202.460
Industrial profitability	276,430	0.370	0.351	0.144
MNEs	270,302	0.432	0.000	0.495
Statutorty corporate tax rate	276,430	0.270	0.263	0.056
Personal income tax rate	276,430	0.469	0.500	0.119
Effective average tax rate	276,430	0.255	0.249	0.065
Effective marginal tax rate	276,430	0.199	0.174	0.091
GDP ($1000,000,000s)	276,430	1,258.121	555.455	1,079.068
Government revenue (%)	276,430	0.474	0.501	0.055
Government expense (%)	276,430	0.494	0.503	0.054

MNEs				
Variables	**Obs**	**Mean**	**Median**	**SD**
Value added ($100,000s)	138,620	299.665	84.811	1,198.926
Cost of employees ($100,000s)	138,620	95.349	27.611	328.974
Number of employees	138,620	178.320	53.000	633.843
Total assets ($100,000s)	138,620	639.234	124.377	5,153.187
Fixed assets ($100,000s)	138,620	316.150	24.028	4,225.328
Tangible fixed assets ($100,000s)	138,620	146.302	12.594	1,490.412
Industrial profitability	138,620	0.369	0.351	0.131
Large firms	138,620	0.157	0.000	0.364
Statutorty corporate tax rate	138,620	0.278	0.295	0.060
Personal income tax rate	138,620	0.440	0.473	0.127
Effective average tax rate	138,620	0.260	0.263	0.064
Effective marginal tax rate	138,620	0.193	0.185	0.094
GDP ($1000,000,000s)	138,620	1,406.037	587.412	1,207.072
Government revenue (%)	138,620	0.467	0.475	0.053
Government expense (%)	138,620	0.489	0.497	0.057

Domestic Firms				
Variables	**Obs**	**Mean**	**Median**	**SD**
Value added ($100,000s)	158,458	62.146	22.984	239.529
Cost of employees ($100,000s)	158,458	22.231	9.050	80.877
Number of employees	158,458	52.148	19.000	211.868
Total assets ($100,000s)	158,458	119.885	37.315	714.517
Fixed assets ($100,000s)	158,458	55.397	9.431	550.857
Tangible fixed assets ($100,000s)	158,458	37.362	4.621	489.319
Industrial profitability	158,458	0.372	0.351	0.151
Large firms	158,458	0.032	0.000	0.175
Statutorty corporate tax rate	158,458	0.263	0.250	0.052
Personal income tax rate	158,458	0.487	0.537	0.111
Effective average tax rate	158,458	0.252	0.246	0.065
Effective marginal tax rate	158,458	0.205	0.171	0.087
GDP ($1000,000,000s)	158,458	1,201.305	555.455	1,021.630
Government revenue (%)	158,458	0.478	0.501	0.055
Government expense (%)	158,458	0.495	0.503	0.052

Appendix D: Additional TFP Measures and Regression Results

In this section, I present additional robustness checks based on alternative productivity measurement, control specifications, and sample construction. First, I construct an alternative firm-level TFP measure using different input–output proxies (Table D1) and re-estimate the baseline regressions in Table 5 using this alternative TFP measure (Table D2). Second, I re-estimate the main specifications excluding control variables (Tables D3–D7). Third, I re-estimate the main regressions on the full unweighted sample, in contrast to the baseline GDP-weighted estimates (Tables D8–D14). Note that in Tables D3–D14, the empirical specifications are re-estimated using the baseline TFP measure.

Alternative TFP Measure with Different Input-Output Proxies

Estimating Capital Stock at Firm Level

In adherence to the Perpetual Inventory Method (PIM), the level of real capital stock k_{it} in firm *i* at time *t* is determined by the level of real capital stock at the immediately preceding time period (k_{it-1}), depreciation rate (σ_{it}), and real investment (I_{it}). This relationship is formally articulated as follows:

$$k_{it} = k_{it-1} \times (1 - \sigma_{it}) + I_{it} \tag{D.1}$$

where real investments are estimated as the disparity between the current and lagged book value of fixed tangible asset, k_{it}^{BV} *and* k_{it-1}^{BV}, plus depreciation, deflated by the country and industry specific deflators

$$I_{it} = (k_{it}^{BV} \; - \; k_{it-1}^{BV} + DP_{it}^{BV})/PI_t \tag{D.2}$$

PI_t is the annual investment price deflator of each country at the 2-digit industry level derived from the Eurostat Database. The depreciation rate is defined as $\sigma_{it} = DP_{it}^{BV} / k_{it-1}^{BV}$

For the first observed year of each firm (t=0), the capital stock is the observed booked value of fixed tangible assets deflated by the price deflators:

$$k_{i0} = k_{i0}^{BV} / PI_0 \tag{D.3}$$

Estimating Alternative TFP

Using this PIM-based capital stock, I re-estimate firm-level TFP from a Cobb–Douglas production function:

$$y_{it} = \alpha_0 + \gamma_l l_{it} + \gamma_k k_{it} + \rho_{it} + \varepsilon_{it}, \tag{D.4}$$

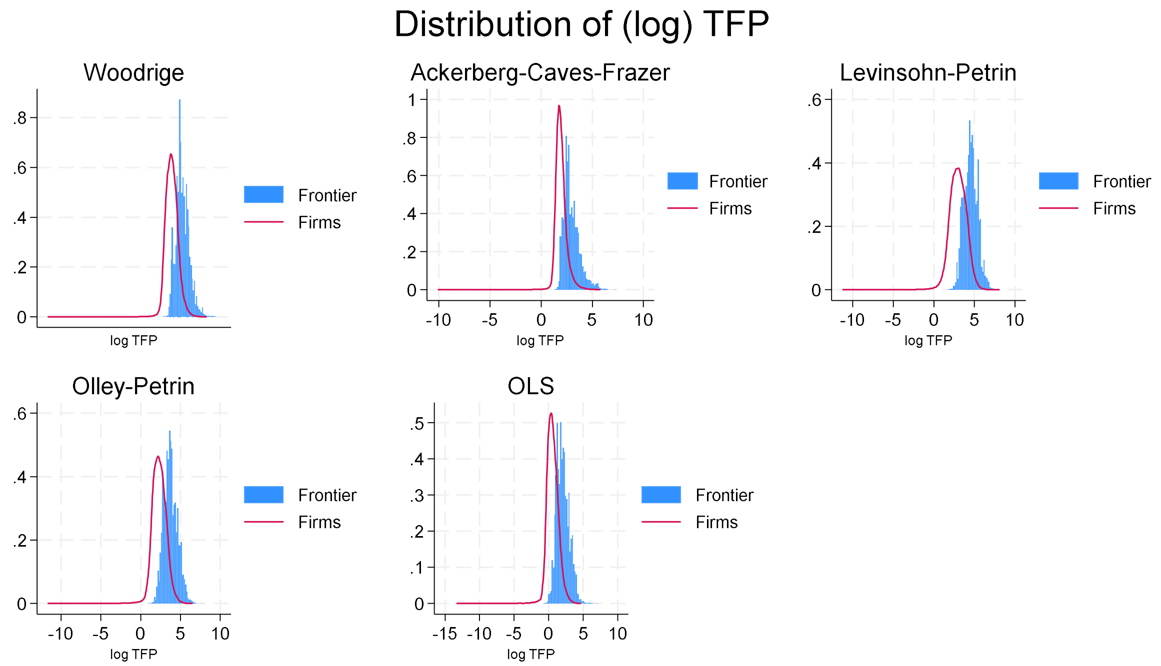
where y_{it} represents the logarithm of turnover, l_{it} denotes the logarithm of total cost of employees, and k_{it} indicates logarithm of the capital stock measured by PIM for each firm *i* in year *t*. All series are deflated using country-industry price index from EU KLEMS/OECD. The corresponding TFP estimates are reported in Table D1 and Figure D1.

Table D1 – Alternative TFP Measures with Different Input-Output Proxies

	Mean (SD)				
	WRDG	ACF	LP	OP	OLS
Firms' TFP estimates (log)	2.435 (0.628)	1.937 (0.536)	2.984 (1.006)	2.349 (0.853)	0.598 (0.806)
Frontiers' TFP estimates (log)	3.521 (0.683)	2.948 (0.757)	4.544 (0.846)	3.751 (0.860)	2.058 (0.910)
TFP gap of frontier to firm (log)	1,078 (0.649)	0.995 (0.671)	1.541 (0.885)	1.380 (0.838)	1.433 (0.874)
Number of Observations					

This table presents the statistics of TFP measured by using the equation $y_{it} = \alpha_0 + \beta l_{it} + \gamma k_{it} + \delta_{it} + \varepsilon_{it}$, at which y_{it} is the (log) value-added output, l_{it} is (log) cost of employees and k_{it} is (log) tangible fixed assets for firm i in year t, δ_{it} represents for TFP, and ε_{it} is white noise. WRDG, ACF, LP, OP, and OLS stands for the Wooldridge, Ackerberg–Caves–Frazer, Levinsohn–Petrin, Olley–Pakes, and Ordinary Least Squares estimator, respectively. The frontier is defined as firms that lie above the 95th percentile of the TFP distribution in each country–industry time period. The TFP gap is calculated based on the ratio of the TFP level of the frontier divided by the TFP level of each individual firm.

Figure D1 – Distribution of (log) TFP of Firm and Frontier with Alternative Input-Output Proxies



Source: Author's own Illustrations

Table D2 – Baseline Results with Alternative Input-Output Proxies

Dependent variable: $\Delta\ln TFP_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln TFP_F$	0.193***	0.193***	0.193***	0.191***	0.071***	0.076***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.003)	(0.004)
lnTFPGap	0.347***	0.393***	0.390***	0.429***	0.090***	0.113***
	(0.014)	(0.024)	(0.031)	(0.033)	(0.016)	(0.017)
CITR	**-0.006**	**0.166***	**0.174***	**0.285*****	**0.323*****	**0.203*****
	(0.051)	**(0.095)**	**(0.098)**	**(0.106)**	**(0.057)**	**(0.058)**
lnTFPGap × CITR		**-0.159***	**-0.153***	**-0.247*****	**-0.049**	**-0.094****
		(0.082)	**(0.083)**	**(0.091)**	**(0.044)**	**(0.048)**
I_{jt}			0.072	0.123*	0.071***	0.009
			(0.069)	(0.067)	(0.024)	(0.025)
lnTFPGap × I_{jt}			0.005	-0.033	0.007	0.007
			(0.056)	(0.051)	(0.017)	(0.018)
GE			0.073	0.107	0.143**	0.141**
			(0.085)	(0.093)	(0.058)	(0.057)
GR			-0.754***	-0.774***	-0.496***	-0.169***
			(0.116)	(0.129)	(0.085)	(0.064)
Observations	189,503	189,503	189,503	167,555	189,503	189,473
Number of Firms	55,033	55,033	48,892	55,033	55,033	55,007
R^2	0.202	0.202	0.203	0.076	0.087	0.202
Adjusted R^2	0.202	0.202	0.203	0.075	0.082	0.202
Firm FE	YES	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	NO	YES	NO
Industry FE	NO	NO	NO	NO	YES	NO
Industry-Country FE	NO	NO	NO	NO	NO	YES

This table presents the baseline results of Equation (3) at which TFP is measured by the Woodridge (WRDG) method with alternative input and output proxies. Specifically, a firm's value-added output is substituted by its turnover, and its capital stock is determined by the standard Perpetual Inventory Method. The dependent variable is the log of TFP growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* in year *t*. I_{jt} is the industrial profitability. GE and GR stand for the total government expenditure and total government revenue, respectively. Appendix B provides detailed variable definitions. All regressions use whole sample, except regression 4 that uses only observations from non-tax haven firms. Regressions 5 and 6 replace the firm fixed effect by country and industry, and country–industry fixed effects, respectively. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

All remaining robustness checks (Tables D3–D14) are conducted using the baseline TFP measure.

Table D3 – Baseline Results with Alternative TFP Measurement Techniques without Control Variables

Dependent variable: $\Delta \ln TFP_i$	ACF (1)	LP (3)	OP (4)	OLS (5)
$\Delta \ln TFP_F$	0.208***	0.233***	0.228***	0.191***
	(0.005)	(0.005)	(0.005)	(0.005)
lnTFPGap	0.457***	0.502***	0.494***	0.431***
	(0.017)	(0.019)	(0.019)	(0.017)
CITR	0.391***	0.357***	0.323***	0.402***
	(0.072)	(0.075)	(0.076)	(0.072)
lnTFPGap × CITR	-0.333***	-0.338***	-0.344***	-0.342***
	(0.058)	(0.064)	(0.065)	(0.057)
Observations	306,755	305,796	305,632	306,882
Number of Firms	80,165	80,281	80,265	80,117
R^2	0.209	0.233	0.229	0.193
Adjusted R^2	0.209	0.233	0.229	0.193
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	NO	NO	NO	NO

This table presents the results of sensitivity tests regarding different TFP measurement methodologies: Regression 1: Ackerberg et al., (ACF); Regression 2: Levinsohn–Petrin (LP) estimator; Regression 3: Olley–Pakes (OP) estimator; and Regression 4: OLS estimator. The dependent variable is the rate of productivity growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. The TFP gap is further categorized into 4 quartiles Appendix B provides detailed variable definitions. All regressions include control variables, firm and year fixed effects. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D4 – Heterogeneity by Firm Size without Control Variables

Dependent variable: $\Delta \ln TFP_i$	Large	SME	Small	Whole sample	Non-tax haven sample
	(1)	(2)	(3)	(4)	(5)
$\Delta \ln TFP_F$	0.116***	0.247***	0.298***	0.102***	0.100***
	(0.012)	(0.006)	(0.008)	(0.004)	(0.003)
lnTFPGap	0.168***	0.543***	0.660***	0.194***	0.208***
	(0.027)	(0.021)	(0.029)	(0.010)	(0.011)
CITR	**-0.049**	**0.455*** **	**0.780*** **	**0.459*** **	**0.555*** **
	(0.109)	**(0.087)**	**(0.135)**	**(0.048)**	**(0.051)**
lnTFPGap × CITR	**0.124**	**-0.397*** **	**-0.522*** **	**-0.220*** **	**-0.266*** **
	(0.102)	**(0.071)**	**(0.101)**	**(0.034)**	**(0.037)**
Large				0.173***	0.191***
				(0.016)	(0.018)
Large × lnTFPGap				-0.120***	-0.123***
				(0.015)	(0.017)
Large × CITR				**-0.357*** **	**-0.411*** **
				(0.054)	**(0.064)**
Large × lnTFPGap × CITR				**0.282*** **	**0.269*** **
				(0.054)	**(0.063)**
Observations	28,290	277,594	193,489	305,883	264,989
Number of Firms	6,386	73,877	54,144	80,262	70,262
R^2	0.146	0.244	0.286	0.099	0.100
Adjusted R^2	0.146	0.244	0.286	0.099	0.100
Firm FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES

This table presents the results of heterogeneity tests regarding firm sizes. *Large* is a dummy variable for large firms at least 250 employees. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: large firms, SMEs (fewer than 250 employees), and small firms (fewer than 50 employees), respectively. Regressions 4 and 5 report the results of Equation (4) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable is the rate of productivity growth in firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D5 – Heterogeneity by Multinational Status without Control Variables

Dependent variables: $\Delta\ln TFP_i$	MNE (1)	Non-haven MNE (2)	Domestic (3)	Full sample (4)	Non-haven sample (5)
$\Delta\ln TFP_F$	0.202***	0.207***	0.263***	0.104***	0.103***
	(0.007)	(0.008)	(0.008)	(0.004)	(0.003)
lnTFPGap	0.340***	0.367***	0.651***	0.235***	0.232***
	(0.022)	(0.026)	(0.033)	(0.014)	(0.014)
CITR	**-0.029**	**0.054**	**0.849*****	**0.703*** **	**0.705*****
	(0.082)	**(0.096)**	**(0.145)**	**(0.064)**	**(0.065)**
lnTFPGap × CITR	**0.027**	**-0.032**	**-0.676*****	**-0.348*****	**-0.334*****
	(0.075)	**(0.089)**	**(0.115)**	**(0.047)**	**(0.048)**
MNE				0.187***	0.160***
				(0.020)	(0.022)
MNE × lnTFPGap				-0.097***	-0.077***
				(0.017)	(0.019)
MNE × CITR				**-0.480*****	**-0.393*****
				(0.069)	**(0.076)**
MNE × lnTFPGap × CITR				**0.283*****	**0.215*****
				(0.059)	**(0.065)**
Observations	139,121	103,740	159,396	298,516	259,427
Number of Firms	33,828	25,622	44,215	78,042	68,614
R^2	0.215	0.224	0.252	0.100	0.101
Adjusted R^2	0.215	0.224	0.252	0.099	0.101
Firm FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Controls	NO	NO	NO	NO	NO

This table presents the results of heterogeneity tests regarding multinational ownerships. MNE is a dummy variable for multinational firms. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: MNEs, non-haven MNEs, and domestic firms, respectively. Regressions 4 and 5 report the results of Equation (5) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable the log of TFP growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier F over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D6 – Robustness Test with Alternative Tax Measures without Control Variables

Dependent variable: $\Delta \ln TFP_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln TFP_F$	0.229***	0.235***	0.229***	0.235***	0.229***	0.235***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
lnTFPGap	0.408***	0.433***	0.390***	0.415***	0.325***	0.350***
	(0.019)	(0.022)	(0.016)	(0.017)	(0.018)	(0.020)
CITR	**0.794*** **	**0.902*** **				
	(0.080)	**(0.088)**				
lnTFPGap x CITR	**-0.772*** **	**-0.805*** **				
	(0.072)	**(0.080)**				
EATR			**-0.047**	**0.094**	**0.221*** **	**0.360*** **
			(0.067)	**(0.075)**	**(0.071)**	**(0.080)**
lnTFPGap x EATR			**0.036**	**-0.013**	**-0.230*** **	**-0.272*** **
			(0.060)	**(0.068)**	**(0.067)**	**(0.075)**
PITR	-0.282***	-0.255***			-0.122**	-0.101*
	(0.052)	(0.059)			(0.051)	(0.057)
lnTFPGap x PITR	0.480***	0.470***			0.310***	0.305***
	(0.041)	(0.045)			(0.040)	(0.044)
Observations	305,884	264,990	305,884	264,990	305,884	264,990
Number of Firms	80,263	70,263	80,263	70,263	80,263	70,263
R^2	0.232	0.239	0.228	0.234	0.230	0.236
Adjusted R^2	0.232	0.239	0.228	0.234	0.230	0.236
Controls	NO	NO	NO	NO	NO	NO

This table reports additional regression results using alternative tax measures. Regressions (1) and (2) use the statutory corporate income tax rate, consistent with the baseline model, while regressions (3)–(6) use the effective average tax rate (EATR). The analysis is based on the full sample (Regressions 1,3, 5) and non-tax haven sample (Regressions 2, 4, 6), and includes firm and year fixed effects. The dependent variable is the log of TFP growth for firm *i* in year *t*. The productivity frontier *F* is defined as the 95th percentile of the TFP distribution within each country–industry–year cell. The TFP gap is measured as the log ratio of TFP at the frontier to the TFP of each individual firm. Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D7 – Robustness Test with Alternative Frontiers without Control Variables

Dependent variables: $\Delta\ln TFP_i$	Highest TFP level		99^{th} Percentile		95^{th} Percentile (EU Single Market)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln TFP_F$	0.046***	0.046***	0.092***	0.095***	0.302***	0.310***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.007)	(0.008)
lnTFPGap	0.224***	0.236***	0.304***	0.325***	0.756***	0.770***
	(0.007)	(0.008)	(0.011)	(0.012)	(0.022)	(0.024)
CITR	**1.159*** **	**1.292*** **	**1.103*** **	**1.252*** **	**0.938*** **	**1.046*** **
	(0.059)	**(0.064)**	**(0.065)**	**(0.072)**	**(0.081)**	**(0.091)**
lnTFPGap x CITR	**-0.446*** **	**-0.482*** **	**-0.472*** **	**-0.521*** **	**-0.664*** **	**-0.679*** **
	(0.022)	**(0.024)**	**(0.034)**	**(0.038)**	**(0.073)**	**(0.080)**
Observations	319,276	274,997	317,702	273,884	310,844	268,737
Number of Firms	82,254	71,745	82,010	71,580	80,789	70,621
R^2	0.065	0.068	0.102	0.107	0.325	0.331
Adjusted R^2	0.065	0.068	0.102	0.107	0.325	0.331
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	NO	NO	NO	NO	NO	NO

This table presents robustness checks using alternative definitions of the productivity frontier. Regressions (1) and (2) define the frontier as the maximum TFP level within each country–industry–year cell. Regressions (3) and (4) use the 99^{th} percentile, while (5) and (6) use the 95^{th} percentile of the TFP distribution within each industry–year cell (regardless of country). All regressions include firm and year fixed effects. Regressions (1), (3), and (5) use the full sample, while (2), (4), and (6) are restricted to firms in non-tax haven jurisdictions. The analysis is based on the full sample and includes firm and year fixed effects. The dependent variable is the log of TFP growth for firm i in year t. The TFP gap is defined as the log ratio of the TFP level at the respective frontier to the TFP of each individual firm. Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table D8 – Baseline Results without Weighting

Dependent variable: $\Delta\ln\text{TFP}_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\ln\text{TFP}_F$	0.299***	0.299***	0.300***	0.309***	0.148***	0.158***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)
lnTFPGap	0.479***	0.503***	0.491***	0.502***	0.178***	0.212***
	(0.008)	(0.022)	(0.025)	(0.027)	(0.011)	(0.013)
CITR	**-0.048**	**0.049**	**0.170****	**0.191****	**0.389*****	**0.290*****
	(0.042)	**(0.082)**	**(0.082)**	**(0.092)**	**(0.044)**	**(0.047)**
lnTFPGap × CITR		**-0.094**	**-0.108**	**-0.096**	**-0.177*****	**-0.235*****
		(0.074)	**(0.073)**	**(0.082)**	**(0.031)**	**(0.038)**
I_{jt}			-0.220***	-0.220***	-0.005	-0.159***
			(0.046)	(0.050)	(0.020)	(0.024)
lnTFPGap × I_{jt}			0.041	0.046	0.041***	0.039**
			(0.037)	(0.040)	(0.016)	(0.017)
GE			0.762***	0.838***	0.365***	0.218***
			(0.072)	(0.081)	(0.047)	(0.049)
GR			-1.024***	-1.084***	-0.404***	-0.018
			(0.086)	(0.096)	(0.062)	(0.050)
Observations	304,410	304,410	304,410	263,746	304,409	304,384
Number of Firms	79,842	79,842	79,842	69,907	79,841	78,823
R^2	0.266	0.266	0.267	0.276	0.104	0.118
Adjusted R^2	0.266	0.266	0.267	0.276	0.103	0.114
Firm FE	YES	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	NO	YES	NO
Industry FE	NO	NO	NO	NO	YES	NO
Industry-Country FE	NO	NO	NO	NO	NO	YES

This table presents the baseline results of Equation (3) at which TFP is measured by the Woodridge (WRDG) method with alternative input and output proxies. Specifically, a firm's value-added output is substituted by its turnover, and its capital stock is determined by the standard Perpetual Inventory Method. The dependent variable is the log of TFP growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* in year *t*. I_{jt} is the industrial profitability. GE and GR stand for the total government expenditure and total government revenue, respectively. Appendix B provides detailed variable definitions. All regressions use whole sample, except regression 4 that uses only observations from non-tax haven firms. Regressions 5 and 6 replace the firm fixed effect by country and industry, and country–industry fixed effects, respectively. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D9 – Baseline Results with Alternative TFP Measurement Techniques without Weighting

Dependent variable: $\Delta \ln TFP_i$	ACF (1)	LP (3)	OP (4)	OLS (5)
$\Delta \ln TFP_F$	0.278***	0.305***	0.300***	0.260***
	(0.005)	(0.005)	(0.005)	(0.004)
lnTFPGap	0.496***	0.491***	0.488***	0.486***
	(0.022)	(0.025)	(0.025)	(0.022)
CITR	**0.245*** **	**0.149***	**0.127**	**0.307*** **
	(0.078)	**(0.083)**	**(0.085)**	**(0.077)**
lnTFPGap × CITR	**-0.206*** **	**-0.094**	**-0.101**	**-0.248*** **
	(0.066)	**(0.074)**	**(0.074)**	**(0.064)**
Observations	305,259	304,323	304,162	305,380
Number of Firms	79,739	79,861	79,842	79,696
R^2	0.250	0.271	0.268	0.237
Adjusted R^2	0.250	0.271	0.267	0.237
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
Controls	YES	YES	YES	YES

This table presents the results of sensitivity tests regarding different TFP measurement methodologies: Regression 1: Ackerberg et al., (ACF); Regression 2: Levinsohn–Petrin (LP) estimator; Regression 3: Olley–Pakes (OP) estimator; and Regression 4: OLS estimator. The dependent variable is the rate of productivity growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. The TFP gap is further categorized into 4 quartiles Appendix B provides detailed variable definitions. All regressions include control variables, firm and year fixed effects. Controls include industry profitability interacted with TFP gap, total government expenditure, and total government revenues (ratio to GDP). *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D10 – Heterogeneity by Firm Size without Weighting

Dependent variable: $\Delta \ln TFP_i$	Large	SME	Small	Whole sample	Non-tax haven sample
	(1)	(2)	(3)	(4)	(5)
$\Delta \ln TFP_F$	0.153***	0.315***	0.356***	0.148***	0.151***
	(0.011)	(0.005)	(0.007)	(0.003)	(0.004)
lnTFPGap	0.176***	0.515***	0.599***	0.193***	0.206***
	(0.036)	(0.027)	(0.036)	(0.012)	(0.013)
CITR	**-0.191**	**0.195****	**0.408*****	**0.421*****	**0.516*****
	(0.123)	**(0.093)**	**(0.137)**	**(0.048)**	**(0.052)**
lnTFPGap × CITR	**0.217**	**-0.104**	**-0.207***	**-0.195*****	**-0.241*****
	(0.138)	**(0.080)**	**(0.110)**	**(0.034)**	**(0.038)**
Large				0.188***	0.202***
				(0.017)	(0.020)
Large × lnTFPGap				-0.117***	-0.117***
				(0.017)	(0.021)
Large × CITR				**-0.362*****	**-0.401*****
				(0.060)	**(0.075)**
Large × lnTFPGap × CITR				**0.253*****	**0.228*****
				(0.063)	**(0.080)**
Observations	27,980	276,430	192,731	304,409	263,745
Number of Firms	6,298	73,544	53,921	79,841	69,906
R^2	0.161	0.278	0.310	0.107	0.110
Adjusted R^2	0.160	0.278	0.310	0.106	0.109
Firm FE	YES	YES	YES	NO	NO
Controls	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES

This table presents the results of heterogeneity tests regarding firm sizes. *Large* is a dummy variable for large firms at least 250 employees. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: large firms, SMEs (fewer than 250 employees), and small firms (fewer than 50 employees), respectively. Regressions 4 and 5 report the results of Equation (4) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable is the rate of productivity growth in firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier *F* over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D11 – Heterogeneity by Multinational Status without Weighting

Dependent variables: ΔlnTFP_i	MNE (1)	Non-haven MNE (2)	Domestic (3)	Full sample (4)	Non-haven sample (5)
ΔlnTFP_F	0.249***	0.257***	0.347***	0.149***	0.153***
	(0.006)	(0.007)	(0.008)	(0.003)	(0.004)
lnTFPGap	0.333***	0.343***	0.603***	0.250***	0.247***
	(0.027)	(0.031)	(0.041)	(0.016)	(0.016)
CITR	**-0.295*****	**-0.296*****	**0.456*****	**0.719*****	**0.732*****
	(0.085)	**(0.101)**	**(0.156)**	**(0.063)**	**(0.065)**
lnTFPGap × CITR	**0.310*****	**0.317*****	**-0.231***	**-0.360*****	**-0.355*****
	(0.080)	**(0.097)**	**(0.129)**	**(0.050)**	**(0.051)**
MNE				0.230***	0.207***
				(0.019)	(0.021)
MNE × lnTFPGap				-0.127***	-0.110***
				(0.017)	(0.019)
MNE × CITR				**-0.594*****	**-0.530*****
				(0.068)	**(0.075)**
MNE × lnTFPGap × CITR				**0.354*****	**0.304*****
				(0.061)	**(0.068)**
Observations	138,620	103,457	158,458	297,077	258,209
Number of Firms	27,284	20,441	35,640	77,633	68,266
R^2	0.225	0.235	0.310	0.109	0.112
Adjusted R^2	0.225	0.235	0.310	0.109	0.111
Firm FE	YES	YES	YES	NO	NO
Year FE	YES	YES	YES	YES	YES
Country FE	NO	NO	NO	YES	YES
Industry FE	NO	NO	NO	YES	YES
Controls	YES	YES	YES	YES	YES

This table presents the results of heterogeneity tests regarding multinational ownerships. MNE is a dummy variable for multinational firms. Regressions 1–3 report the results of Equation (3) with firm and year fixed effects for specific sub-samples: MNEs, non-haven MNEs, and domestic firms, respectively. Regressions 4 and 5 report the results of Equation (5) with county, industry, and year fixed effects for the whole sample and the non-haven sample, respectively. The dependent variable the log of TFP growth of firm *i* in year *t*. The frontier *F* is defined as the 95th percentile of the TFP distribution in each country–industry–year cell. The TFP gap is measured as the log of the ratio of TFP at the frontier F over TFP of firm *i* in industry *j*, country *c* and year *t*. Appendix B provides detailed variable definitions. *, **, and *** indicate statistical significance at the levels of 10, 5, and 1 percent, respectively. Standard errors are clustered at the firm level and are reported in parentheses.

Table D12 – Robustness Test with Alternative Tax Measures without Weighting

Dependent variable: $\Delta \ln TFP_i$	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln TFP_F$	0.295***	0.304***	0.300***	0.309***	0.297***	0.306***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnTFPGap	0.442***	0.449***	0.364***	0.377***	0.301***	0.311***
	(0.024)	(0.027)	(0.024)	(0.026)	(0.024)	(0.026)
CITR	1.090***	1.075***				
	(0.105)	(0.117)				
lnTFPGap x CITR	-1.002***	-0.950***				
	(0.101)	(0.112)				
EATR			-0.315***	-0.294***	0.240**	0.260**
			(0.078)	(0.089)	(0.097)	(0.109)
lnTFPGap x EATR			0.425***	0.430***	-0.154	-0.140
			(0.075)	(0.085)	(0.097)	(0.109)
PITR	-0.467***	-0.445***			-0.286***	-0.283***
	(0.058)	(0.065)			(0.058)	(0.064)
lnTFPGap x PITR	0.678***	0.652***			0.484***	0.478***
	(0.048)	(0.052)			(0.046)	(0.050)
Observations	305,884	264,990	305,884	264,990	305,884	264,990
Number of Firms	80,263	70,263	80,263	70,263	80,263	70,263
R^2	0.232	0.239	0.228	0.234	0.230	0.236
Adjusted R^2	0.232	0.239	0.228	0.234	0.230	0.236
Controls	YES	YES	YES	YES	YES	YES

This table reports additional regression results using alternative tax measures. Regressions (1) and (2) use the statutory corporate income tax rate, consistent with the baseline model, while regressions (3)–(6) use the effective average tax rate (EATR). The analysis is based on the full sample (Regressions 1,3, 5) and non-tax haven sample (Regressions 2, 4, 6), and includes firm and year fixed effects. The dependent variable is the log of TFP growth for firm *i* in year *t*. The productivity frontier *F* is defined as the 95th percentile of the TFP distribution within each country–industry–year cell. The TFP gap is measured as the log ratio of TFP at the frontier to the TFP of each individual firm. All egressions also control for industry profitability interacted with the TFP gap, total government expenditure, and government revenue (as a share of GDP). Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

Table D13 – Robustness Test with Alternative Frontiers without Weighting

Dependent variables: $\Delta \ln TFP_i$	Highest TFP level		99th Percentile		95th Percentile (EU Single Market)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \ln TFP_F$	0.081***	0.082***	0.148***	0.156***	0.319***	0.330***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
lnTFPGap	0.247***	0.266***	0.347***	0.369***	0.711***	0.707***
	(0.010)	(0.011)	(0.013)	(0.015)	(0.031)	(0.032)
CITR	**1.172*** **	**1.293*** **	**0.960*** **	**1.041*** **	**1.045*** **	**1.052*** **
	(0.063)	**(0.069)**	**(0.073)**	**(0.083)**	**(0.095)**	**(0.104)**
lnTFPGap x CITR	**-0.449*** **	**-0.498*** **	**-0.398*** **	**-0.430*** **	**-0.577*** **	**-0.510*** **
	(0.025)	**(0.028)**	**(0.040)**	**(0.045)**	**(0.084)**	**(0.091)**
Observations	317,766	273,720	316,202	272,617	309,208	267,379
Number of Firms	81,829	71,385	81,586	71,221	80,343	70,247
R^2	0.090	0.093	0.143	0.151	0.330	0.339
Adjusted R^2	0.090	0.093	0.143	0.151	0.330	0.339
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES

This table presents robustness checks using alternative definitions of the productivity frontier. Regressions (1) and (2) define the frontier as the maximum TFP level within each country–industry–year cell. Regressions (3) and (4) use the 99th percentile, while (5) and (6) use the 95th percentile of the TFP distribution within each industry–year cell (regardless of country). All regressions include controls for industry profitability interacted with the TFP gap, total government expenditure, and government revenue (as a share of GDP), along with firm and year fixed effects. Regressions (1), (3), and (5) use the full sample, while (2), (4), and (6) are restricted to firms in non-tax haven jurisdictions. The analysis is based on the full sample and includes firm and year fixed effects. The dependent variable is the log of TFP growth for firm i in year t. The TFP gap is defined as the log ratio of the TFP level at the respective frontier to the TFP of each individual firm. Variable definitions are detailed in Appendix B. Standard errors are clustered at the firm level and reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Impressum:
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Sitz des Vereins: Berlin

Herausgeber: Kay Blaufus, Jochen Hundsdoerfer, Martin Jacob, Dirk Kiesewetter, Rolf J. König, Lutz Kruschwitz, Andreas Löffler, Ralf Maiterth, Heiko Müller, Jens Müller, Rainer Niemann, Deborah Schanz, Sebastian Schanz, Caren Sureth-Sloane, Corinna Treisch

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ISSN 1861-8944