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Boon or Bane? On Productivity and Environmental Regulation

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Abstract: As climate change has gained more attention in the last decade, effects of environmental regulation on productivity are important to design green tax reforms. This study examines the impacts of environmental taxes and spillovers on technical efficiency, using data on Central European manufacturing firms, from 2009 to 2017. The results highlight strong effects of environmental taxation on productivity. Besides, downstream energy taxation does not affect productivity, while upstream taxes decrease technical efficiency. Downstream pollution taxation decreases productivity, whereas upstream taxation spurs technical efficiency. This study contributes to the literature by investigating heterogeneous tax effects across industries, involving tax spillovers and considering endogeneity issues.

JEL: L51, H23

Keywords: Economic Regulation, Environmental Taxes and Subsidies

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1.1 Introduction

The choice of environmental policy instruments has been extensively debated since the seminal contribution of Pigou (1920) on using taxes and subsidies to internalize welfare losses caused by externalities. The environmental economics literature distinguishes between 'command and control' (CAC) approaches (e.g. environmental protection amendments) and 'market based incentives' (MBI) (e.g. environmental taxes, tradable permits). Although economic theory preferred MBIs because of their cost effectiveness, CAC has been the major instrument for a long time. During the 1990s, MBIs became more popular, i.e.: environmental taxes in the beginning of the 1990s and tradable permits in the late 1990s (e.g. the Kyoto protocol in 1997) (Norregaard & Reppelin-Hill (2000)). Currently, environmental taxes are enjoying a renaissance (Ewa Krukowska (2020)).
While almost every microeconomic textbook covers the basic models of environmental policy's welfare implications in first-best and second-best worlds, economic theory and empirical evidence on its effects on firm behaviour and performance are sparse and provide conflicting guidance, though being fundamental for designing green tax reforms. First, the 'pollution haven hypothesis' claims that firms relocate to countries with weak environmental standards when environmental taxes rise, reducing profits, productivity and inputs by limiting production possibilities (Commins *et al.* (2011)). Conversely, the 'factor endowment hypothesis' suggests that employing available clean natural resources improves production possibilities and productivity (Copeland & Taylor (2004)). Similarly, the 'Porter hypothesis' asserts that environmental regulation spurs firms to innovate, increasing productivity and investment (Porter (1991), Porter & Van der Linde (1995)). To provide empirical evidence on these conflicting hypothesis, I examine the impacts of environmental taxes on company performance and behaviour employing micro-data on Central European manufacturing firms from 2009 to 2017.

Many empirical studies examine the environmental benefits of climate policies, while only few studies, primarily undertaken at country- or industry-level, analyse impacts of environmental policy on firm behaviour. Leiter *et al.* (2011) investigate effects of industry expenditure on environmental protection and country-level environmental tax revenue on firm investment, and find positive, but diminishing effects. Enevoldsen *et al.* (2007) estimate responses of competitiveness and output to energy taxes and find significantly negative impacts, whereas Henderson & Millimet (2005) observe insignificant impacts of environmental stringency on state-level output. Next, Aziz *et al.* (2021) conclude that environmental policy stringency negatively affects economic growth in the short-run, but positively in the long run. Besides, Franco & Marin (2017) investigate how environmental tax rates and their spillovers affect innovation and efficiency.
Conversely, only few studies employ firm-level data. Fujii *et al.* (2016) identify technical innovators in the area of CO_2 emissions using Chinese firm-level data. Martin *et al.* (2014) observe insignificant effects of carbon taxation on British manufacturing firms' employment, gross output and productivity, and observe significantly negative impacts on energy intensity and electricity use. Similarly, Yang *et al.* (2021) find significantly negative effects of tightening SO_2 removal rates on Chinese firm- and industry-level productivity. In contrast, Commins *et al.* (2011) find

positive effects of energy taxes on productivity and returns on capital, negative impacts on employment, and mixed effects on investment of European firms. Broberg *et al.* (2013) regress Swedish manufacturing firms' productivity on distributed lags of investment in pollution control and prevention, rejecting the Porter hypothesis. Supporting the Porter hypothesis, Lanoie *et al.* (2008) find negative short-run and positive long-run impacts of environmental policy stringency on technical efficiency of Quebec's manufacturing firms. Managi *et al.* (2005) investigate the impact of environmental policy on technical efficiency of the offshore oil and gas industry and confirm the Porter hypothesis. Last, Lundgren *et al.* (2015) estimate the efficiency impacts of CO_2 taxes on Swedish pulp and paper manufacturers, partially observing significantly positive effects.
This work contributes to the available literature in several aspects. First, my dataset also covers smaller firms next to large or listed firms enabling a more comprehensive analysis. Second, I allow heterogeneous effects of environmental tax rates across industries. Third, to the best of my knowledge, this is the first study examining downstream and upstream environmental tax spillovers using firm-level data. Fourth, I consider endogeneity of environmental tax rates by employing lags instead of contemporaneous values.

Generally, energy and pollution tax rates significantly impact productivity in many industries. Positive impacts of taxes on productivity are observed in energy-intensive sectors, industries producing energy-consuming goods and polluting sectors, whereas negative impacts are estimated in industries declining in Europe. Conversely, input amounts significantly respond in fewer industries. Downstream energy tax rates do not affect productivity, while upstream ones decrease technical efficiency. Downstream pollution taxation decreases productivity, whereas upstream taxation spurs technical efficiency.

The paper proceeds as follows. *Section 1.2* introduces the empirical framework and data, used to examine the impacts of environmental regulation on firm behaviour, while *Section 1.3* provides the results of the production function estimations and the regressions of firm behaviour. Last, *Section 1.4* sums up and draws conclusions.

1.2 Empirical strategy and data

1.2.1 First stage: estimation of the production function

To establish links between environmental regulation and productivity, a two-stage procedure is employed. Following the literature (e.g. Gemmell *et al.* (2018), Richter & Schiersch (2017), Collard-Wexler & De Loecker (2015), Lu & Yu (2015), Du *et al.* (2014), Del Bo (2013), Doraszelski & Jaumandreu (2013), Crinò & Epifani (2012), De Loecker & Warzynski (2012), Arnold *et al.* (2011), De Loecker (2007a), Javorcik (2004)), I estimate three-input revenue-based Cobb-Douglas production functions, as described in equation (1), with the method by Ackerberg *et al.* (2015) explained in appendix A. y denotes logged output (dependent variable), k logged capital (state variable), l logged labour (free variable), and m logged material (proxy variable). ζ is the sum of unobserved productivity ω and measurement errors of productivity shocks ψ. Indices i and t represent firms and years. A Cobb-Douglas specification is chosen, as it is probably the most popular type in the literature, although translog specifications are more flexible, though data demanding (Syverson (2011)).

$$y_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + \underbrace{\omega_{i,t} + \psi_{i,t}}_{\zeta_{i,t}} \tag{1}$$

As product-level output and input quantities are usually not available, while monetary outputs and inputs are mostly provided as firm-level aggregates, I follow the literature and estimate gross output production functions using producers' real total monetary outputs and inputs. Firm-level data are sourced from the Orbis database published by Bureau van Dijk. Orbis contains accounting data, legal form, industry activity codes, and incorporation date for a large set of public and private companies worldwide. I include active and inactive; medium sized, large and very large [1] European manufacturing companies (NACE C1000 - C3320), incorporated in five countries: Austria, the Czech Republic, Hungary, Slovakia and Slovenia. The final sample is a nine-year unbalanced panel dataset, from 2009 to 2017, containing 18,060 firms with 123,101 observations of 24 two-digit NACE industries (94 three-digit and 265 four-digit NACE industries). [2]

Output is defined as real operating revenues, being the sum of net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk (2007)) deflated by annual gross value added deflators from the OECD database [3], varying across countries, two-digit NACE industries and years. Next, capital is approximated with tangible fixed assets (e.g.: machinery) deflated by uniform investment good price indexes from the same database [4], varying across countries and years. Third, labour is a physical measure of the number of employees included in the company's payroll. Fourth, material is measured by real material expenditures, being the sum of expenditures on raw materials and intermediate goods deflated by uniform intermediate good price indexes from the same database [4], varying across countries and years. Fifth, real investment is approximated by exploiting the law of motion of capital, i.e.: depreciation, deflated by the same price index as capital, and first differences in firm-specific real tangible assets are summed (Castelnovo *et al.* (2019), Richter & Schiersch (2017), Newman *et al.* (2015), Du *et al.* (2014), Nishitani *et al.* (2014), Baghdasaryan & la Cour (2013), Javorcik & Li (2013), Crinò & Epifani (2012), Higón & Antolín (2012), Javorcik (2004)).

[1] Orbis considers firms to be 'medium sized', when operating revenues $\geq$ 1 mill. EUR or total assets $\geq$ 2 mill. EUR or employees $\geq$ 15. Orbis defines firms to be 'large', when operating revenues $\geq$ 10 mill. EUR or total assets $\geq$ 20 mill. EUR or employees $\geq$ 150. Firms are 'very large', when operating revenues $\geq$ 100 mill. EUR or total assets $\geq$ 200 mill. EUR or employees $\geq$ 1,000 or the company is listed (Bureau van Dijk (2007)).

[2] Observations with implausible output and input values (e.g. negative values, values almost zero), missing values, unknown activity status or industry affiliation are dropped.

[3] `https://stats.oecd.org/Index.aspx?DataSetCode=SNA_TABLE6A`

[4] `https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI`

To consider heterogenous input elasticities β across countries, I follow the majority of studies (e.g. Fons-Rosen *et al.* (2021), Levine & Warusawitharana (2021), Gemmell *et al.* (2018), Olper *et al.* (2016)) and estimate equation (1) for each two-digit NACE industry-country combination. As productivity is the residual, it measures the shifts in output while keeping inputs constant. Owing to the logged dependent variable, productivity is also logged, as shown in equation (2) (Javorcik (2004), Olley & Pakes (1996)).

$$log(TFP_{i,t}) = y_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \tag{2}$$

1.2.2 Second stage: determinants of firm behaviour

In the second stage, I examine the effects of environmental policy on firm behaviour. Instead of employing first-differencing as Commins *et al.* (2011), I use fixed effects regressions, as described in equation (3), primarily used in the literature (e.g. Castelnovo *et al.* (2019), Franco & Marin (2017)). The indices i, t, s and c denote firms, years, two-digit NACE industries and countries, with S and C being the total numbers of two-digit NACE industries and countries. e and p represent the energy and pollution tax rates.

$$\begin{aligned} w_{i,t} = & \sum_{s=1}^{S} \delta_{e,s} \cdot D_s \cdot energy\,tax\,rate_{c,s,t-2} \\ & + \sum_{s=1}^{S} \delta_{p,s} \cdot D_s \cdot pollution\,tax\,rate_{c,s,t-2} \\ & + \phi_e \cdot downstream\,energy\,tax\,rate_{c,s,t-2} + \rho_e \cdot upstream\,energy\,tax\,rate_{c,s,t-2} \\ & + \phi_p \cdot downstream\,pollution\,tax\,rate_{c,s,t-2} + \rho_p \cdot upstream\,pollution\,tax\,rate_{c,s,t-2} \\ & + \beta \cdot X_{c,i,s,t-1} + \alpha_i + \sum_{c=1}^{C} \sum_{t=2010}^{2017} \gamma_{c,t} \cdot D_c \cdot D_t + \epsilon_{i,t} \end{aligned} \tag{3}$$

The dependent variables, w, cover logged productivity, real investment, real material expenditures and employment. Tax rates are introduced in levels to avoid losing zero-value observations when logging them (Franco & Marin (2017), Lundgren *et al.* (2015)). Like Commins *et al.* (2011), I estimate the effects of energy and pollution tax rates for each two-digit NACE industry by interacting them with dummies for two-digit NACE industries D_s. *Table* B.1 in appendix B lists all two-digit NACE industries' codes and names. Given the log-level representation, coefficients $\delta_{e,s}$ and $\delta_{p,s}$ quantify the dependent variables' environmental tax rate semi-elasticities for each two-digit NACE industry.

I source data on energy and pollution tax revenues starting from 2008, in Euro, from Eurostat

(Franco & Marin (2017), Commins *et al.* (2011)). [5] [6] Energy taxes cover taxes on energy production and products (e.g. petrol; diesel; electricity; biofuels; CO_2 etc.), while pollution taxes include taxes related to emissions to air and water, management of waste and noise (e.g. NO_X; SO_X; other emissions (excluding CO_2); pesticides; artificial fertilisers; packaging etc.) (Eurostat (2020)). Resource and transport taxes are excluded due to multicollinearity. Tax revenues, varying across countries, two-digit NACE industries and years, are divided by nominal gross values added from the same database [7], varying at the same level, to compute average tax rates (Franco & Marin (2017), Commins *et al.* (2011)).

Following Franco & Marin (2017), I involve tax rates paid by all downstream and upstream industries (including agriculture, mining, services) [8] of the same country, since governments try to homogenize tax rates to avoid capital flights. Downstream spillovers are defined as weighted averages of tax rates paid by downstream sectors. I construct the weights from symmetrical input-output tables of the year 2010 [9] provided by Eurostat (Du *et al.* (2014)). [10] For each country, the weighting matrix is calculated as follows. First, the main diagonal is set to zero to avoid double counting and multicollinearity. Second, matrices are row-normalized to obtain weights for every two-digit NACE industry-country combination. Third, they are multiplied with the country-specific tax rate vectors. Conversely, upstream tax rates define weighted averages of environmental tax rates paid by suppliers and are calculated analogously, except that the matrix's transpose is row-normalized. Like Franco & Marin (2017), regulations embodied in imports and exports are excluded, as matrices only cover domestic flows. Tax spillovers are not interacted with industry dummies to avoid multicollinearity.

Concerning endogeneity, two issues are worth discussing. First, endogeneity may be caused by reverse causality. Although the literature (e.g. Franco & Marin (2017), Broberg *et al.* (2013), Commins *et al.* (2011), Lanoie *et al.* (2008), Managi *et al.* (2005)) usually employs distributed lags (including contemporaneous values) of environmental policy stringency (e.g. taxes, pollution abatement control expenditures, emissions) treating them as exogenous, governments set tax rates to affect firms' future production processes. To overcome this problem, Franco & Marin (2017) involve environmental taxes lagged by one year arguing that, in contrast to emissions and pollution abatement control expenditures, governments set environmental tax rates exogenously. Since lagging tax rates by one year might still not suffice, I lag tax rates by two years to break reverse causality. Second, I introduce important drivers of reorganization within firms, firm-level fixed effects and nested country-year dummies to solve omitted variable biases implied by confounding factors.

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[5] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=env_ac_taxind2&lang=en`

[6] Generally, environmental tax rates, control variables, value added deflators and symmetric input-output tables are aggregated at the country and two-digit NACE industry-level. For some industries, however, data are only available at a higher-order group-level, i.e.: for the industries C10, C11 and C12, the covariates are only available as a sum across the three industries. The same holds for the industries C13-C15 and C31-C32.

[7] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=de`

[8] Due to missing values in the weighting matrices, sectors L, T and U, and industry G47 are excluded. For some industries, data is only available at the sector-level (B, D, F, I, O, P) or group-level (C10-C12, C13-C15, C31-C33, E37-E39, J59-J60, J62-J63, M69-M70, M74-M75, N80-N82, Q87-Q88, R90-R92).

[9] Annual data are only provided for Austria, while for the countries data is supplied every five years. This might be a minor issue, as weights obtained for Austria are quite constant across years. Furthermore, country-specific weights constructed from the 2010's and 2015's tables are similar.

[10] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=naio_10_cp1700&lang=de`

If environmental tax rates affect productivity and inputs negatively, the pollution haven hypothesis is supported. Contrarily, positive effects of environmental regulation on productivity and investment favour the Porter hypothesis. Last, the factor endowment hypothesis suggests positive impacts on productivity due to reorganization of production processes (Commins *et al.* (2011)).

Vector X introduces control variables, capturing other drivers of technological progress and reorganization within firms. They are lagged by one period to overcome reverse causality (Franco & Marin (2017), Inui *et al.* (2012)). [11] As employment also responds to wage costs, labour market regulation and human capital, I involve logged firm-level average real wages (Del Bo (2013)). In comparison, Commins *et al.* (2011) employ shares of aggregate labour costs in value added and Franco & Marin (2017) logged industry-specific average wages, but they suffer from multicollinearity. Data on firm-level wage costs are obtained from Orbis, deflated by country-level HCPIs sourced from Eurostat [12] and divided by firm-level employment. Given these studies, I expect them to affect productivity positively, as more human capital makes firms more productive, and employment negatively due to higher costs.
Besides, I introduce two variables capturing the degrees of foreign and domestic competition. First, I include import penetration (Commins *et al.* (2011)), varying across countries, two-digit NACE industries and years. As databases only provide country-level data, I approximate industry-specific pendants with shares of imports in the total supply of goods. The latter is defined as the sum of foreign (imports) and domestic supply (value added). Data on two-digit NACE industry-specific imports, denoted in US dollar, are obtained from the OECD database [13] and converted to Euro employing exchange rates from the Austrian National Bank. [14] [15]
Second, I involve inverted Herfindahl-Hirschman indexes (HHI), $1 - HHI$, and their squares (Atayde *et al.* (2021), Aghion *et al.* (2015)). Franco & Marin (2017) introduce the share of firms with more than 250 employees, but OECD data suffer from missing observations. I calculate the variable, being a number between zero (monopoly) and one (perfect competition), from firm-level real operating revenues for every country, three-digit NACE industry and year. Given the literature (e.g. Inui *et al.* (2012), Van Reenen (2011), Aghion *et al.* (2005)), I expect a concave relationship, as fiercer competition spurs firms to innovate, but also discourages innovation by deteriorating post-entry rents.

Furthermore, I include fixed effects for firms α_i, capturing unobserved firm-level heterogeneity (e.g. country, NACE industry, company size, legal form). Unlike including country-level controls as Commins *et al.* (2011), I involve nested country-year dummies $D_c \cdot D_t$, capturing these countrywide shocks (e.g. profit taxes, electricity and fuel prices, institutional quality, business activity).

[11] Relevant variables are usually influenced by contemporaneous productivity, i.e.: short-run rises in productivity will decrease imports and intensify competition in the same year, as they are newly determined every year.

[12] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de

[13] https://stats.oecd.org/Index.aspx?DataSetCode=TEC1_REV4#

[14] https://www.oenb.at/isaweb/report.do;jsessionid=31BAE0E7828A28A2607F23FE67871C76?report=2.14.5

[15] Though data is available for all two-digit NACE industries, imports are aggregated at the same level as GDP to calculate shares. For the group C11-C13, C13 is excluded due to missing values.

1.3 Results

In the first stage, I estimate production functions to construct productivity for every firm and year, while, in the second stage, I regress $log(TFP)$ and other dependent variables using fixed effects models. Summary statistics are shown in *Table* C.1 in appendix C.

1.3.1 Estimation of the production function

Tables D.1-D.5 in appendix D summarize the results of the production function estimations for each two-digit NACE industry-country combination. In every table, columns (1)-(3) provide the elasticities of output with respect to the considered inputs. Columns (4) and (5) display the numbers of observations and firms. The sum of input elasticities supplies an estimate of the degree of returns to scale. Therefore, column (6) shows the p-value of the Wald tests examining whether this sum significantly differs from one. In some industries, too few firms exit the market not allowing to consider attrition. Column (7), thus, provides information on whether attrition can be and is considered or not. [16]

Overall, results are consistent with the literature (e.g. Richter & Schiersch (2017), Lu & Yu (2015), Du *et al.* (2014), Arnold *et al.* (2011)). Labour elasticities mostly vary between 0.20 and 0.40 (Richter & Schiersch (2017), Arnold *et al.* (2011)). In some industries, coefficients lie between 0.05 and 0.20 as in Lu & Yu (2015) and Du *et al.* (2014). As in these studies, capital elasticities are usually small between 0 and 0.10. In Hungary, some of them, however, are larger, suggesting that the relevant industries produce more capital-intensively. Depending on the study, material elasticities vary between 0.40 and 0.90, confirming my results.
Nevertheless, there are some abnormalities. Particularly, three coefficients exceed one (Austria C23; Slovenia C14) and, similarly to Lu & Yu (2015), the elasticity of capital falls below zero in eight industries (Austria C18, C24 and C28; Czech Republic C18 and C30; Hungary C16; Slovakia C26; Slovenia C33).

1.3.2 Effects of environmental taxes and spillovers

Tables 1 and 2 display the estimates of equation (3). Columns (1)-(4) show the results of the regressions of logged productivity, real investment, real material expenditures and employment. Standard errors are clustered at the firm-level to overcome residual serial correlation. [17]
The first block of *Table* 1 displays energy tax rate semi-elasticities for each two-digit industry, $\delta_{e,s}$, the second block those for the pollution tax rate, $\delta_{p,s}$. Given the small values, pollution tax rates are denoted in per mill. In column (1), the energy tax rate semi-elasticity in industry C16

[16] I exclude tobacco (C12) and coke and petroleum (C19) industries because of too few observations. Industries with less than 15 firms whose analysis does not allow to consider attrition are also dropped due to not-meaningful results.

[17] To check whether results are driven by industries with abnormal production function estimates, I exclude relevant industry-country combinations. The results, however, barely change.

equals 0.0680, meaning that productivity increases by 6.80%, when energy tax rates increase by one percentage point. In the same column, the pollution tax rate semi-elasticity in industry C16 is -0.0145, suggesting that productivity declines by 1.45%, when the pollution tax rate increases by one per mill. *Figures* 1-4 illustrate them graphically. Dots represent the point estimate, lines the 95%-confidence intervals, and stars the significance levels. The first block of *Table* 2 shows the effects of tax spillovers, ϕ and ρ, and the last block the controls' effects. Small values of energy tax rates are found in the industries C10-C11, C13-C15, C18, C21-C22, C25-C28 and C30-C33 with means and maximum values mostly below 0.5 and one percentage point, sometimes resulting in larger coefficients. For these industries, interpreting the coefficients as effects of a rise by one per mill or one-tenth of a per mill (C18, C21, C26-C27) is more adequate, i.e.: if the energy tax rate in industry C10 increases by one per mill, dependent variables change by -1.41, 0.58, -0.42 and -0.98%. Pollution tax rates' coefficients are higher in C13-C15, C21, C25, C27 and C30 with means and maximum values mostly below 0.07-0.3 and 0.7 per mill, suggesting an interpretation as the effects of an increase by one-tenth of a per mill or a smaller unit (C13-C16, C21, C25-C28, C30, C33), i.e.: if the pollution tax rate in industry C13 rises by one-tenth of a per mill, dependent variables change by 3.18, -2.25, -0.75 and 4.43%.

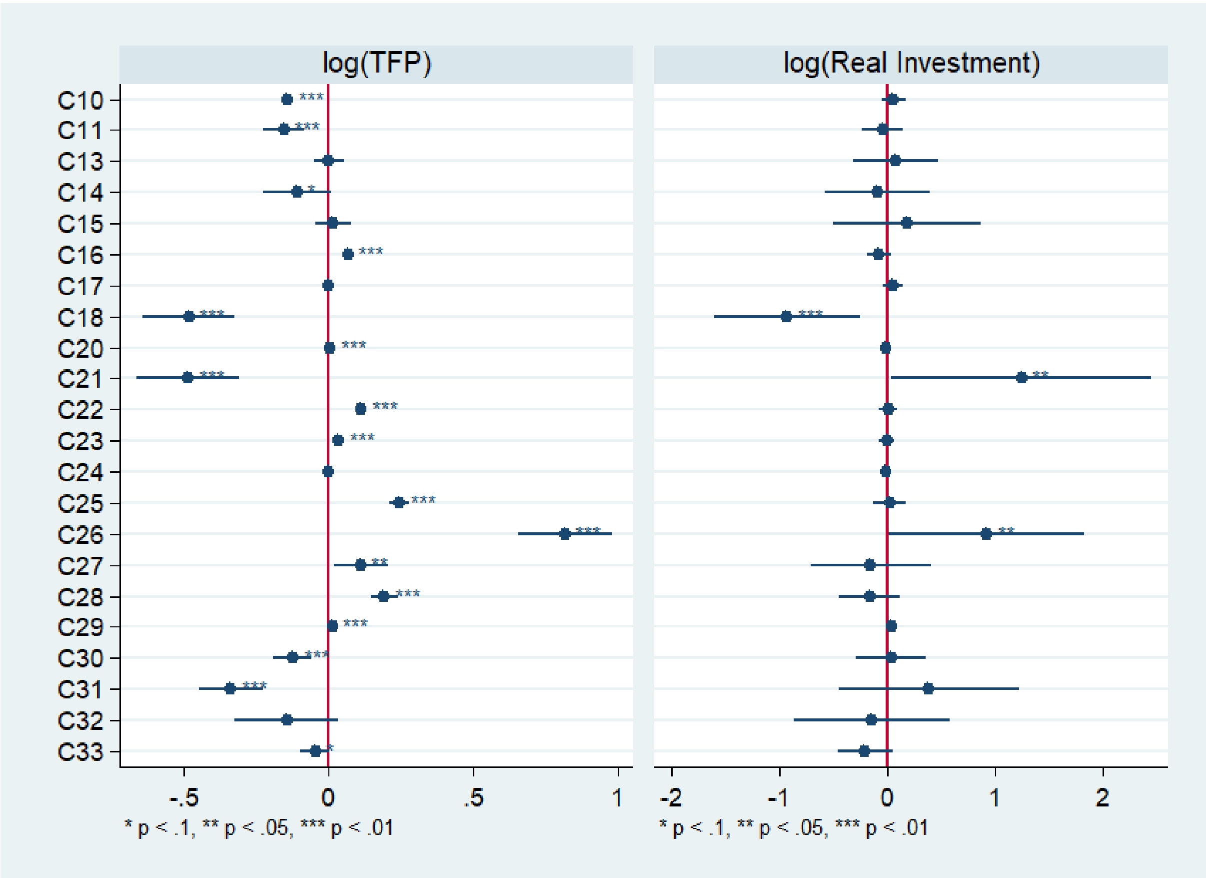

Figure 1: Impacts of energy tax rates on productivity and real investment by industry

Raising energy tax rates in the chemicals (C20), metal processing (C25) and motor vehicle (C29) industries results in productivity gains, as firms significantly purchase more material and employment, favoring the factor endowment hypothesis. Keeping input amounts constant, energy tax rates change some other production processes in the wood (C16), rubber and plastics (C22),

	Dependent Variable:			
	$log(TFP)$	$log(Real\,Investment)$	$log(Real\,Material\,Expenditures)$	$log(Employment)$
	(1)	(2)	(3)	(4)
$\delta_{e,\,s}$				
C10	−0.1407***	0.0581	−0.0422**	−0.0984***
	(0.0090)	(0.0575)	(0.0207)	(0.0205)
C11	−0.1535***	−0.0444	−0.0457	−0.0583
	(0.0357)	(0.0975)	(0.0552)	(0.0500)
C13	0.0030	0.0792	0.0919	0.0827
	(0.0273)	(0.2023)	(0.0755)	(0.0526)
C14	−0.1081*	−0.0872	−0.0860*	−0.0388
	(0.0602)	(0.2489)	(0.0513)	(0.0402)
C15	0.0174	0.1893	0.1200*	−0.0023
	(0.0305)	(0.3477)	(0.0691)	(0.0559)
C16	0.0680***	−0.0748	0.0101	−0.0137
	(0.0072)	(0.0563)	(0.0185)	(0.0170)
C17	0.0030	0.0544	0.0012	0.0128
	(0.0085)	(0.0443)	(0.0175)	(0.0139)
C18	−0.4815***	−0.9274***	−0.0451	0.1374
	(0.0816)	(0.3433)	(0.1526)	(0.1022)
C20	0.0057***	−0.0059	0.0040**	0.0012
	(0.0013)	(0.0048)	(0.0019)	(0.0019)
C21	−0.4853***	1.2435**	0.1549	0.1106
	(0.0902)	(0.6142)	(0.2385)	(0.2074)
C22	0.1156***	0.0088	−0.0134	−0.0048
	(0.0078)	(0.0411)	(0.0172)	(0.0141)
C23	0.0348***	−0.0042	0.0015	−0.0158
	(0.0072)	(0.0367)	(0.0240)	(0.0129)
C24	0.0013	−0.0085	0.0053	0.0012
	(0.0016)	(0.0105)	(0.0043)	(0.0031)
C25	0.2461***	0.0236	0.0659*	0.1166***
	(0.0178)	(0.0783)	(0.0363)	(0.0296)
C26	0.8195***	0.9244**	0.1707	0.0182
	(0.0830)	(0.4632)	(0.1893)	(0.1276)
C27	0.1128**	−0.1525	−0.0458	−0.0068
	(0.0472)	(0.2846)	(0.1154)	(0.0716)
C28	0.1940***	−0.1628	0.0273	0.0150
	(0.0241)	(0.1444)	(0.0620)	(0.0432)
C29	0.0140***	0.0384	0.0300*	−0.0052
	(0.0043)	(0.0276)	(0.0168)	(0.0109)
C30	−0.1224***	0.0355	−0.0233	0.0066
	(0.0339)	(0.1630)	(0.0752)	(0.0654)
C31	−0.3352***	0.3883	0.1100	−0.1431
	(0.0561)	(0.4275)	(0.1288)	(0.1165)
C32	−0.1434	−0.1452	−0.0157	0.1516
	(0.0913)	(0.3689)	(0.1777)	(0.1455)
C33	−0.0453*	−0.2049	−0.0851	−0.0074
	(0.0256)	(0.1313)	(0.0535)	(0.0357)
$\delta_{p,\,s}$				
C10	0.0259***	−0.0496**	−0.0208**	0.0004
	(0.0035)	(0.0200)	(0.0096)	(0.0075)
C11	0.0362***	−0.0962*	−0.0224	−0.0011
	(0.0117)	(0.0510)	(0.0220)	(0.0130)
C13	0.3184***	−0.2249	−0.0750	0.4428*
	(0.1152)	(0.7016)	(0.3084)	(0.2539)
C14	0.7623**	1.4917**	0.4285**	0.4732***
	(0.3023)	(0.6967)	(0.1872)	(0.1795)
C15	0.3614***	0.3004	0.2126	0.0784
	(0.1363)	(0.8660)	(0.2194)	(0.2212)
C16	−0.0145***	0.0042	0.0115	0.0106
	(0.0044)	(0.0348)	(0.0116)	(0.0120)
C17	0.0001	0.0045	0.0007	0.0003
	(0.0010)	(0.0075)	(0.0021)	(0.0014)
C18	0.0258***	−0.0242	−0.0172**	−0.0196***
	(0.0043)	(0.0268)	(0.0067)	(0.0056)
C20	0.0154***	−0.0167	0.0056	0.0073
	(0.0038)	(0.0214)	(0.0089)	(0.0062)
C21	−0.1195	−1.2157	−0.2077	0.4281
	(0.1603)	(1.1372)	(0.4561)	(0.3277)
C22	0.0167***	0.0045	0.0058	0.0004
	(0.0039)	(0.0222)	(0.0112)	(0.0078)
C23	0.0109	0.0440	0.0118	0.0396***
	(0.0067)	(0.0693)	(0.0158)	(0.0106)
C24	0.0105***	0.0110	0.0114	0.0004
	(0.0037)	(0.0256)	(0.0104)	(0.0075)
C25	−0.6258***	−0.5536*	−0.4655***	−0.5513***
	(0.0594)	(0.3154)	(0.1429)	(0.0987)
C26	0.0053	0.0136	−0.0013	0.0043
	(0.0054)	(0.0326)	(0.0124)	(0.0096)
C27	−0.3693***	0.1646	−0.0918	0.0681
	(0.0358)	(0.2863)	(0.0937)	(0.0604)
C28	0.0143***	−0.0066	0.0154	0.0099
	(0.0046)	(0.0406)	(0.0120)	(0.0064)
C29	0.0639***	0.0916	0.0284	0.0049
	(0.0091)	(0.0824)	(0.0266)	(0.0161)
C30	0.0307	0.2138	0.4636*	0.1424
	(0.0961)	(0.6451)	(0.2449)	(0.1869)
C31	0.0310***	0.0019	−0.0155	0.0092
	(0.0063)	(0.0536)	(0.0172)	(0.0148)
C32	0.0191*	0.0317	0.0349	−0.0221
	(0.0108)	(0.0473)	(0.0230)	(0.0149)
C33	−0.0622	−0.0040	−0.0586	−0.0542
	(0.0388)	(0.1595)	(0.0651)	(0.0597)

Table 1: Results of the fixed effects regressions (I)

	Dependent Variable:			
	log(TFP)	*log(Real Investment)*	*log(Real Material Expenditures)*	*log(Employment)*
	(1)	(2)	(3)	(4)
ϕ & ρ				
Energy tax rate downstream	−0.0005	0.0048	0.0030	0.0040
	(0.0016)	(0.0074)	(0.0035)	(0.0029)
Energy tax rate upstream	−0.0113 * **	−0.0084	0.0011	0.0003
	(0.0021)	(0.0097)	(0.0035)	(0.0032)
Pollution tax rate downstream	−0.0133 * *	−0.0619*	0.0034	−0.0115
	(0.0059)	(0.0356)	(0.0138)	(0.0094)
Pollution tax rate upstream	0.0279 * **	0.0090	−0.0083	−0.0241 * **
	(0.0045)	(0.0294)	(0.0087)	(0.0067)
Controls				
Log(avg real wage)	0.0625 * **	0.0018	0.0326 * **	−0.1586 * **
	(0.0050)	(0.0181)	(0.0105)	(0.0100)
Import penetration	−0.0021 * **	−0.0003	−0.0007	−0.0017 * **
	(0.0003)	(0.0016)	(0.0007)	(0.0005)
Inverted HHI	0.2924*	−0.0884	−0.0042	0.2016
	(0.1499)	(0.4531)	(0.3117)	(0.1943)
Squared inverted HHI	−0.3003 * **	0.0619	0.0579	−0.0812
	(0.1132)	(0.3684)	(0.2272)	(0.1486)
R-squared	0.063	0.052	0.048	0.083
Observations	100184	86943	100184	99345
Units	16809	16532	16809	16612
Firm-FE & Country-Year Dummies	*yes*	*yes*	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the firm-level. Variance inflation factors (VIFs) are computed manually from the within-R2s of fixed effects regressions of each covariate on the other covariates, firm-level fixed effects and nested country-year dummies, using the data from 2010 to 2017. Observations of 2009 are dropped due to the lagged variables. VIFs of tax rates, varying between 1 and 2 for utmost all variables, do not suggest multicollinearity. Also rejecting multicollinearity, VIFs of the upstream energy and downstream and upstream pollution tax rates, however, are slightly larger around 3.25. On the other hand, the VIFs of the inverted HHI are around 10 due to the inclusion of its squared term suggesting multicollinearity, but decrease severely when excluding its square. For industries C12 and C19, coefficients are not obtainable, as the both industries suffer from too small sample sizes. *p<0.1; **p<0.05; ***p<0.01			

Table 2: Results of the fixed effects regressions (II)

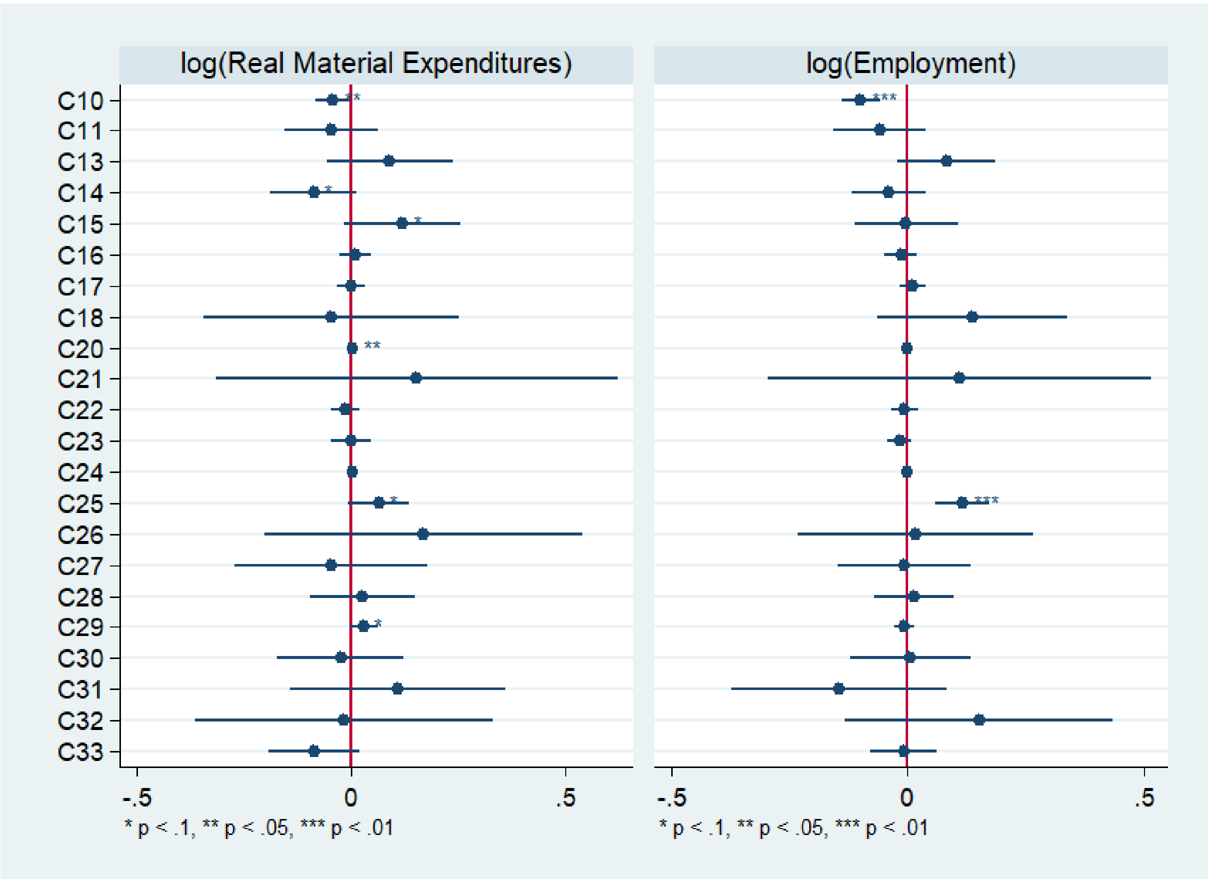

Figure 2: Impacts of energy tax rates on real material expenditures and employment by industry

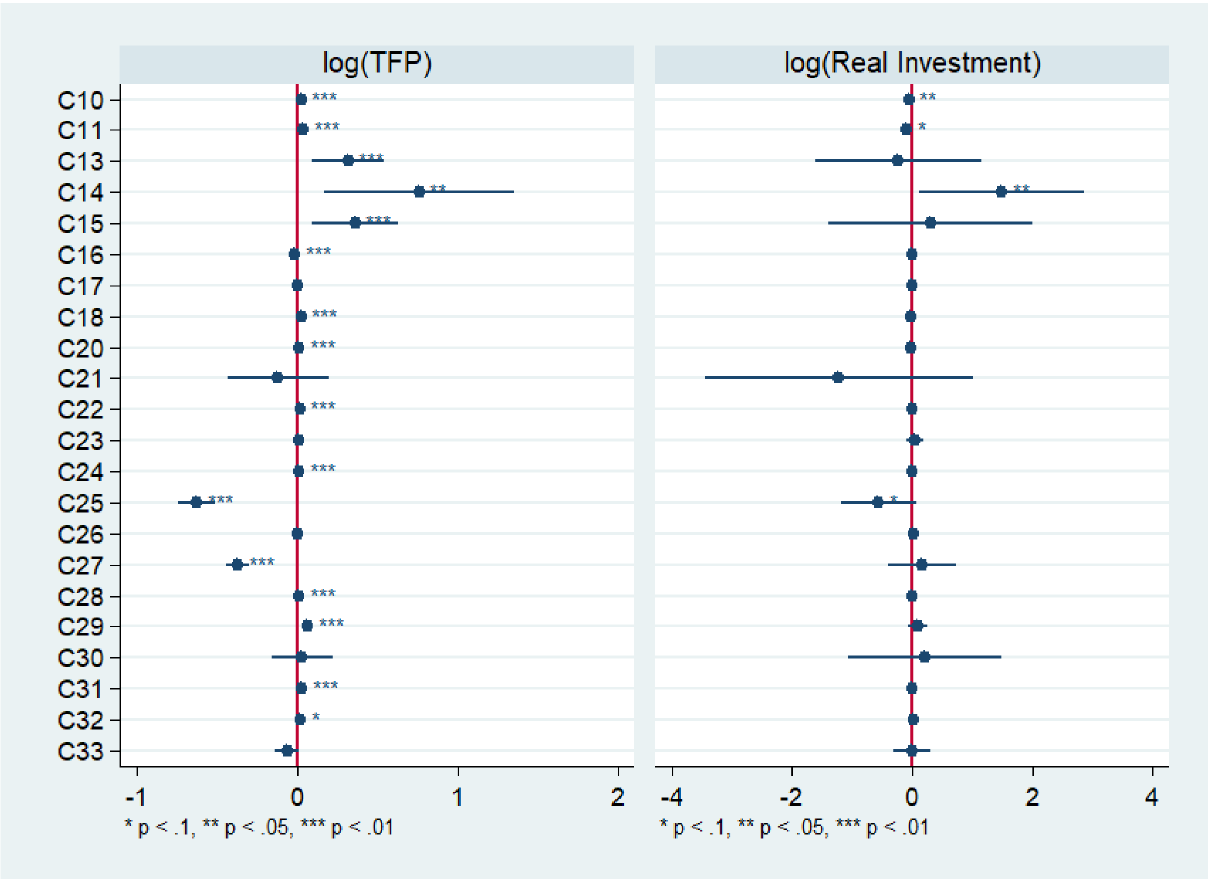

Figure 3: Impacts of pollution tax rates on productivity and real investment by industry

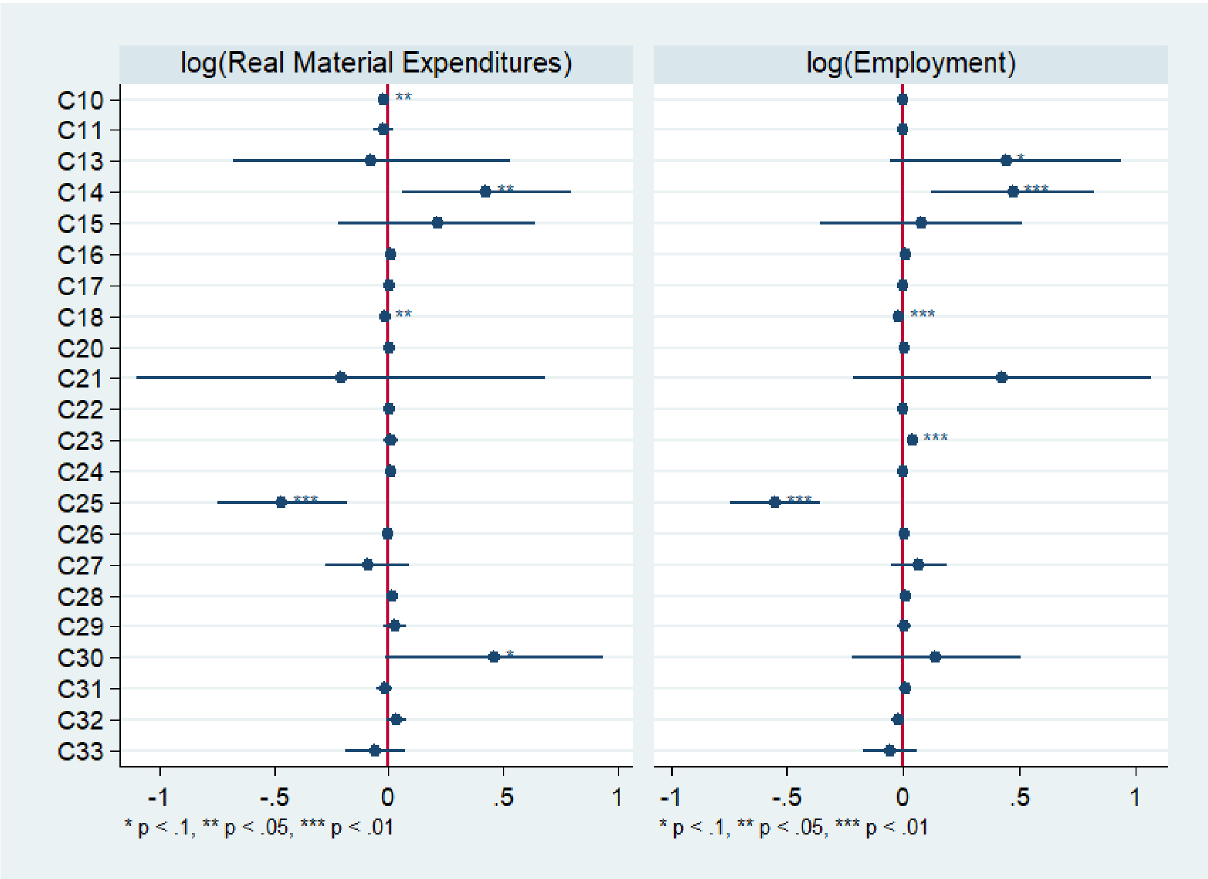

Figure 4: Impacts of pollution tax rates on real material expenditures and employment by industry

non-metallic minerals (C23), electrical equipment (C27) and machinery (C28) sectors, supporting the factor endowment hypothesis. Confirming the Porter hypothesis, firms operating in the electronics industry (C26) expand investment and material, implying efficiency gains. Plausibly, these industries benefit from productivity gains, because they operate energy-intensively (C20, C23, C24) or produce energy-using goods (C25-29). Higher tax rates raise production costs, forcing firms to innovate. Nonetheless, I cannot reject other explainations, as energy taxes can serve as entry barriers or reduce input price volatility (Yang *et al.* (2021), Richter & Schiersch (2017), Fujii *et al.* (2016), Commins *et al.* (2011)).
Higher energy tax rates spur firms to reduce inputs in the food (C10), wearing apparel (C14) and printing and media (C18) industries, causing efficiency losses and, thus, favouring the pollution haven hypothesis. Although the pollution haven hypothesis suggests that environmental policy decreases productivity and input amounts, relocating to other countries is costly. Hence, firms will comply with new regulations by adjusting production processes (e.g. purchasing larger input amounts, substituting inputs with each other), which is observable for the beverages (C11), pharmaceutics (C21), other transport equipment (C30), furniture (C31) and repair and installation (C33) industries. Relevant sectors are declining in Europe (C14, C21, C30-31), spurring this trend, or produce energy-intensively, but are not able to sufficiently reduce energy intensity (C10 and C11 due to cooking and cooling, C14 due to drying, C18) (UBA (2019), UBA (2013c), UBA (2013d), Commins *et al.* (2011)).

In the food (C10), beverages (C11) and printing and media (C18) industries, companies cut inputs, when governments raise pollution taxes, resulting in efficiency gains and suggesting the factor endowment hypothesis. Confirming the factor endowment hypothesis, corporations in the textiles sector (C13) purchase larger input amounts and enjoy productivity gains. Keeping input amounts constant, other production processes are adjusted in the leather (C15), chemicals (C20), rubber and plastics (C22), metal (C24), machinery (C28), motor vehicle (C29), furniture (C31), and other manufacturing (C32) industries. These findings support the factor endowment hypothesis. When raising pollution tax rates in the wearing apparel industry (C14), firms employ larger amounts of every input, favouring the Porter hypothesis. Plausibly, relevant industries benefit from efficiency gains, as they pollute water and air and rely extensively on chemicals next to being energy-intensive (C10, C11, C14, C15, C20, C24) and producing energy consuming products (C28, C29) (UBA (2019), Richter & Schiersch (2017), UBA (2013a), UBA (2013c), UBA (2013b)).
Conversely, in the metal processing sector (C25), companies reduce all inputs when pollution tax rates rise, implying productivity losses and favouring the pollution haven hypothesis. Companies operating in the wood (C16) and electrical equipment (C27) industries adjust aspects of production processes other than inputs, decreasing technical efficiency. Rising production costs, resulting from higher taxes, cannot be compensated by technological progress that fast (C16 and C25 are already obliged to filter emissions (UBA (2014), UBA (2013d)), but searching for environmentally friendly substitutes takes long) and, therefore, firms lose rents.

Concerning the spillovers, Franco & Marin (2017) find significantly positive effects of downstream total environmental tax rates and significantly negative ones of upstream total environmental tax rates on sector-level value added and productivity arguing that downstream taxes spur sellers to innovate, while upstream tax raises hamper innovation. Although energy taxes make up the largest share of total environmental taxes, my results partially confirm their conclusion. For instance, energy taxes can be shifted to customers more easily than other taxes (Commins *et al.* (2011)). Hence, tax raises induce consumers to buy less and sellers, therefore, purchase less from their suppliers, reducing demand, but providing incentives to innovate and implying an insignificant effect of downstream taxation. Conversely, suppliers may shift rising taxes to customers who might not be able to sufficiently innovate or substitute inputs, implying efficiency losses to buyers and a negative effect of upstream taxes. Interpreted as elasticities, raising downstream or upstream energy tax rates by one percentage point results in changes of the dependent variables by -1.33-+0.48%. Contrarily, the opposite holds for pollution tax rates. Higher upstream taxes might spur suppliers to innovate, as they cannot easily shift the tax, also benefiting their customers and resulting in a significantly positive effect of upstream taxation. As customers might face difficulties when shifting taxes to their customers, they may shift them to suppliers, implying a significantly negative impact of downstream taxes. When increasing downstream or upstream pollution tax rates by one per mill, dependent variables change by -6.19-+2.79%.

Like Commins *et al.* (2011), average real wages significantly increase productivity, as more human capital allows to produce more efficiently, and decreases employment due to higher costs. Consequently, employment is substituted with material. If the variable rises by 1%, dependent variables change by -0.16-+0.06%. In comparison, import penetration significantly decreases employment due to the more intense competition from foreign countries. Consequently, productivity decreases, as demand for domestic products declines. An increase by one percentage point, reduces dependent variables by 0.03-0.21%. As expected, the funtional form of the relationship between domestic competition and productivity diplays the concave shape, as competition boosts productivity in a less competitive market, but reduces efficiency growth in highly competitive industries (Inui *et al.* (2012), Van Reenen (2011), Aghion *et al.* (2005)).

1.3.3 Discussion

The overriding goal of green tax reforms is to design competitive, efficient and environmentally friendly markets. Nonetheless, green tax reforms, aiming to achieve productive and allocative efficiency, are a Herculean task due to the trade-off between productive efficiency and climate protection. This study sheds light on the impacts of environmental taxation and its spillovers on firm behaviour and performance, and highlights strong effects on productivity. In many industries, firms adjust production processes, suggesting that regulation induces innovation. Developing new technologies and innovating, however, takes more time in particular industries such that firms lose rents.

Concerning the magnitudes, effects of energy tax rates are not directly comparable with those by Commins *et al.* (2011). First, they only involve energy tax rates as the single variables of interest and exclude real material expenditures and tax spillovers. Second, they estimate elasticities, while I regress semi-elasticities. Third, production functions are estimated differently. Fourth, they introduce country-level control variables, while I employ nested country-year dummies. Fifth, I use fixed effects regressions considering endogeneity of environmental policy instead of employing first-differencing treating policy variables as exogenous. Nonetheless, I observe fewer significant effects on input amounts, but the results generally, as productivity responds positively to taxation in industries that are energy-intensive or polluting, produce energy consuming products or rely heavily on chemicals, while negative effects are observed in industries declining in Europe. Concerning energy tax rates, my results are in line with Fujii *et al.* (2016) who conclude that energy conservation laws raised productivity in the metals and machinery sectors. My results confirm those by Broberg *et al.* (2013) in the sense that the Porter hypothesis does not hold for European manufacturing sectors. Though Franco & Marin (2017) use total environmental tax rates and sector-level data, the results for energy taxation, making up the largest part of the former, partially agree.

However, one set of econometric issues results from employing deflated monetary output values instead of quantities. Potential differences in input prices across firms, originating from differences in the access to input markets or monopsonies, might cause 'input price biases' (negatively biased coefficients, upwards biased productivity). Like the literature, I implicitly assume that all firms of a given country face identical input prices. In case of input price differences, my estimates suffer from input price biases, because I rely on two deflated monetary inputs (De Loecker & Goldberg (2014)).
Last, another set of econometric issues stems from using deflated monetary values of output instead of quantities, called 'omitted price variable bias'. Unfortunately, price indices are only available at industry-level, while firm-level or product-level price indices would be required. Applying industry-level price indices to firm-level operating revenues implies biased production function coefficients, if product- or firm-level prices deviate from the development of industry-level price indexes, which are captured by the error term. The direction of each coefficient's bias is not straightforward and can go in either direction (De Loecker & Goldberg (2014), De Loecker (2007b), Klette & Griliches (1996)). To solve this problem, in the spirit of Klette & Griliches (1996), De Loecker (2007b) proposes a framework, based on including industry-specific aggregate demand shifters, which, however, fails to correctly identify coefficients, because multiplying all asymmetrically biased input coefficients with a constant cannot yield unbiased coefficients (Ornaghi (2006)).

1.4 Conclusion

I investigate the effects of environmental taxes on firm behaviour to provide policy lessons for designing green tax reforms. Therefore, in the first stage, Cobb-Douglas production functions are estimated with the algorithm by Ackerberg *et al.* (2015), using data on Central European manufacturing firms, from 2009 to 2017. In the second stage, I estimate the impacts of environmental taxation on productivity and firm behaviour with fixed effects models.

The results show that productivity significantly responds in many industries that are energy-intensive or polluting, produce energy consuming products, rely heavily on chemicals or are declining in Europe. In few industries, the pollution haven hypothesis holds, while other industries respond by substituting inputs with each other, purchasing larger input amounts or changing other processes, thereby decreasing productivity, as relocating to other countries is not easy. Downstream energy tax rates do not affect productivity, while upstream ones decrease technical efficiency. Downstream pollution taxation decreases productivity, whereas upstream taxation spurs technical efficiency. Policy makers should consider significantly negative impacts of environmental taxes and their spillovers on productivity. First, I suggest to implement green tax reforms raising environmental tax rates to spur innovation and, consequently, technical efficiency. Second, I recommend to complement them with the introduction of investment incentives, wage tax cuts or other compensations to bolster negative impacts on productivity, investment and employment.

Appendices

A The method by Ackerberg/Caves/Frazer

When estimating production functions, much consideration needs to be given to identification problems. First, simultaneity biases arise because of endogeneous inputs, i.e.: firms with positive productivity shocks demand larger input amounts. Second, attrition in the data causes identification problems, because firms with high productivity levels have higher probabilities to survive, while firms with low levels of productivity are more likely to exit the market (Olley & Pakes (1996)).

Unlike Olley & Pakes (1996) and Levinsohn & Petrin (2003), Ackerberg *et al.* (2015) allow for a dynamic specification in the choice of labour by claiming that labour also depends on unobserved productivity. Hence, the coefficients of free variables (e.g. labour) cannot be correctly identified in the first stages of Olley & Pakes (1996) and Levinsohn & Petrin (2003). Instead, the coefficients are estimated in the second stage. To get the intuition, imagine a subperiod between periods $t-1$ and t. Firstly, the firm chooses the optimal amount of material. Secondly, the productivity shock occurs in the subperiod. Thirdly, the amount of labour is purchased. Now, labour is an element of the demand function for material in period t, which is still invertible as long as m is strictly increasing in productivity.

In the first stage, I run

$$y_{i,t} = \phi_{i,t}(l_{i,t}, k_{i,t}, m_{i,t}) + \psi_{i,t} \tag{A.1}$$

to obtain estimates for the expected output $\hat{\phi}_{i,t}$ and the productivity shock $\hat{\psi}_{i,t}$. The expected output is

$$\phi_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + h_t^{-1}(m_{i,t}, k_{i,t}) \tag{A.2}$$

with $h^{-1}(.)$ being the inverted demand for material (proxy variable). Assuming that the demand for material is strictly monotonically increasing in productivity allows to invert the demand function to obtain productivity as a function of the proxy and state variables. Then, unobserved productivity ω is substituted with the inverted function, giving equation (A.2).

In the second stage, estimates for all production function coefficients $\beta = (\beta_k, \beta_l, \beta_m$ are calculated by relying on the law of motion of productivity

$$\omega_{i,t} = g_t(\omega_{i,t-1}) + \xi_{i,t} \tag{A.3}$$

using equation (A.4).

$$\omega_{i,t}(\beta) = \phi_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \tag{A.4}$$

Non-parametrically regressing $\omega(\beta)$ on its lag recovers the innovations to productivity ξ, required to form moment conditions, used to estimate the coefficients β with GMM. To obtain the standard errors of β, I rely on cluster bootstrapping.

$$\begin{aligned} E[\xi_{i,t} \cdot k_{i,t}] &= 0 \\ E[\xi_{i,t} \cdot l_{i,t-1}] &= 0 \\ E[\xi_{i,t} \cdot m_{i,t-1}] &= 0 \end{aligned} \tag{A.5}$$

B Industry codes

Two-digit NACE industry	Name
C10	food products
C11	beverages
C12	tobacco products
C13	textiles
C14	wearing apparel
C15	leather and related products
C16	wood and products of wood and cork, except furniture; articles of straw and plaiting materials
C17	paper and pulp products
C18	printing and reproduction of recorded media
C19	coke and refined petroleum products
C20	chemicals and chemical products
C21	basic pharmaceutical products and preparations
C22	rubber and plastics products
C23	other non-metallic mineral products
C24	basic metals
C25	fabricated metal products, except machinery and equipment
C26	computer, electronic and optical products
C27	electrical equipment
C28	machinery and equipment n.e.c.
C29	motor vehicles, trailers and semi-trailers
C30	other transport equipment
C31	furniture
C32	other manufacturing
C33	repair and installation of machinery and equipment

Table B.1: Two-digit NACE industry codes

C Descriptives

D Estimates of the first stage

Variable	Unit	Mean (SD)	Min - Med - Max	IQR (CV)
log(TFP)		4.4 (2.1)	-37.7 < 4.2 < 13.9	1.9 (0.5)
Real Operating Revenues	Mill. Euro	22.2 (168.2)	0 < 3.1 < 14089.2	8.9 (7.6)
Real Material Expenditures	Mill. Euro	13.7 (123.7)	0 < 1.4 < 10179.1	4.6 (9)
Real Tangible Assets	Mill. Euro	9.3 (1301.3)	0 < 0.8 < 452504.6	2.7 (140.1)
Number Employees	Integer	127 (334.8)	1 < 38 < 15000	110 (2.6)
Real Investment	Mill. Euro	1 (2028.4)	-452498.1 < 0.1 < 452501	0.4 (2029)
Energy Tax Rate	Percentage Point	1.5 (3.6)	0 < 0.7 < 48.8	0.8 (2.5)
Energy Tax Rate Downstream	Percentage Point	1.8 (1.1)	0 < 1.5 < 6.6	1.4 (0.6)
Energy Tax Rate Upstream	Percentage Point	3.2 (1.6)	0.6 < 2.8 < 13	2 (0.5)
Pollution Tax Rate	Per Mill	0.6 (1.7)	0 < 0.1 < 36.3	0.3 (2.9)
Pollution Tax Rate Downstream	Per Mill	0.4 (0.6)	0 < 0.2 < 3.7	0.5 (1.3)
Pollution Tax Rate Upstream	Per Mill	0.7 (0.8)	0 < 0.4 < 8.6	0.7 (1.1)
Average Real Wage	Euro	18833.3 (172487.4)	0.3 < 14265.5 < 48415712	10152.6 (9.2)
Import Penetration	Percentage Point	44.7 (15)	0 < 43.2 < 90.8	15.3 (0.3)
Inverted HHI		0.9 (0.1)	0 < 0.9 < 1	0.1 (0.2)
Note:	'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, 'IQR' the interquartile range and 'CV' the coefficient of variation.			

Table C.1: Descriptive statistics

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.361*** (0.456)	0.044** (0.018)	0.578*** (0.084)	367	97	0.57	*yes*
C11 beverages	*NA* *NA*	*NA* *NA*	*NA* *NA*	53	15	*NA*	*no*
C13 textiles	0.266*** (0.022)	0.061*** (0.018)	0.660*** (0.013)	91	24	0.09	*yes*
C14 wearing apparel	*NA* *NA*	*NA* *NA*	*NA* *NA*	26	10	*NA*	*no*
C15 leather	*NA* *NA*	*NA* *NA*	*NA* *NA*	27	6	*NA*	*no*
C16 wood products	0.406*** (0.028)	0.086 (0.060)	0.513*** (0.105)	197	56	0.89	*no*
C17 paper and pulp products	0.220 (0.272)	0.033 (0.045)	0.823 (1.014)	134	28	1.00	*no*
C18 printing and recorded media	0.598 (1.269)	−0.090** (0.037)	0.557 (1.086)	98	25	1.00	*yes*
C20 chemicals and chemical products	0.444*** (0.128)	0.124** (0.061)	0.239 (0.205)	213	53	0.58	*yes*
C21 pharmaceutical products	0.158*** (0.017)	0.046 (0.072)	0.812*** (0.031)	88	21	0.84	*yes*
C22 rubber and plastics products	0.216*** (0.000)	0.054*** (0.000)	0.706*** (0.000)	209	57	0.00	*yes*
C23 other non-metallic mineral products	0.576*** (0.097)	0.173*** (0.034)	1.541*** (0.260)	237	67	0.00	*yes*
C24 basic metals	0.485*** (0.000)	−0.051*** (0.000)	0.664*** (0.000)	273	58	0.00	*yes*
C25 fabricated metal products	0.566*** (0.010)	0.001 (0.019)	0.452*** (0.080)	451	137	0.92	*yes*
C26 computer, electronic, optical products	0.697 (0.563)	0.083 (0.076)	0.068 (0.053)	230	64	0.82	*yes*
C27 electrical equipment	0.204*** (0.008)	0.057** (0.027)	0.682*** (0.018)	172	46	0.00	*yes*
C28 machinery	0.388*** (0.058)	−0.034 (0.055)	0.625*** (0.025)	548	145	0.84	*yes*
C29 motor vehicles, trailers, semi-trailers	0.211 (0.184)	0.055 (0.048)	0.719 (0.629)	148	37	1.00	*yes*
C30 other transport equipment	*NA* *NA*	*NA* *NA*	*NA* *NA*	33	9	*NA*	*no*
C31 furniture	0.136*** (0.019)	0.043* (0.023)	0.737*** (0.087)	61	20	0.45	*yes*
C32 other manufacturing	0.597*** (0.018)	0.038 (0.039)	0.550*** (0.016)	70	24	0.00	*yes*
C33 repair, installation	0.879*** (0.068)	0.055 (0.045)	0.225*** (0.035)	63	19	0.02	*no*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table D.1: Results of production function estimation for Austria

Industry	Labour	Capital	Material	Number Observations	Number Firms	p-Value CRS	Attrition
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
C10 food products	0.145***	0.101***	0.768***	4,859	719	0.08	*yes*
	(0.004)	(0.024)	(0.013)				
C11 beverages	0.160***	0.113	0.827***	886	127	0.01	*yes*
	(0.021)	(0.072)	(0.012)				
C13 textiles	0.319*	0.111*	0.551*	1,238	181	1.00	*yes*
	(0.169)	(0.059)	(0.293)				
C14 wearing apparel	0.312***	0.055***	0.611***	814	130	0.00	*yes*
	(0.007)	(0.018)	(0.010)				
C15 leather	0.435***	0.087*	0.499***	267	42	0.76	*yes*
	(0.032)	(0.045)	(0.034)				
C16 wood products	0.238***	0.074**	0.668***	2,387	352	0.26	*yes*
	(0.009)	(0.036)	(0.008)				
C17 paper and pulp products	0.244***	0.052***	0.746***	1,159	164	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C18 printing and recorded media	0.387***	−0.011	0.539***	1,323	191	0.00	*yes*
	(0.011)	(0.026)	(0.014)				
C20 chemicals and chemical products	0.210***	0.153**	0.595***	1,666	216	0.21	*yes*
	(0.012)	(0.061)	(0.017)				
C21 pharmaceutical products	0.160***	0.115**	0.683***	347	44	0.28	*no*
	(0.055)	(0.046)	(0.117)				
C22 rubber and plastics products	0.277***	0.059***	0.692***	4,933	669	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C23 other non-metallic mineral products	0.184***	0.120***	0.714***	2,572	355	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C24 basic metals	0.255***	0.029	0.721***	1,268	177	0.86	*yes*
	(0.018)	(0.049)	(0.010)				
C25 fabricated metal products	0.295***	0.083***	0.601***	11,977	1,751	0.01	*yes*
	(0.003)	(0.016)	(0.005)				
C26 computer, electronic, optical products	0.338***	0.054***	0.634***	1,741	236	0.01	*yes*
	(0.004)	(0.016)	(0.005)				
C27 electrical equipment	0.357***	0.055***	0.572***	3,645	500	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C28 machinery	0.284***	0.052***	0.663***	7,172	960	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C29 motor vehicles, trailers, semi-trailers	0.364***	0.020	0.659***	2,701	363	0.00	*yes*
	(0.005)	(0.018)	(0.003)				
C30 other transport equipment	0.259***	−0.013	0.740***	728	97	0.50	*yes*
	(0.008)	(0.032)	(0.012)				
C31 furniture	0.197***	0.033*	0.756***	1,554	228	0.38	*yes*
	(0.009)	(0.017)	(0.007)				
C32 other manufacturing	0.352***	0.023	0.614***	1,511	228	0.28	*yes*
	(0.005)	(0.018)	(0.002)				
C33 repair, installation	0.421***	0.029	0.546***	3,388	507	0.70	*yes*
	(0.013)	(0.024)	(0.004)				
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table D.2: Results of production function estimation for Czech Republic

Industry	Labour	Capital	Material	Number Observations	Number Firms	p-Value CRS	Attrition
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
C10 food products	0.283***	0.180***	0.504***	2,801	428	0.08	*yes*
	(0.011)	(0.036)	(0.014)				
C11 beverages	0.504	0.054	0.568	580	90	0.89	*yes*
	(0.442)	(0.046)	(0.503)				
C13 textiles	0.352***	0.149**	0.502***	315	55	1.00	*yes*
	(0.134)	(0.072)	(0.080)				
C14 wearing apparel	0.443***	0.035	0.340***	312	48	0.00	*yes*
	(0.019)	(0.030)	(0.016)				
C15 leather	0.299***	0.169***	0.490***	166	23	0.00	*yes*
	(0.019)	(0.060)	(0.030)				
C16 wood products	0.291***	−0.076	0.720***	425	73	0.05	*yes*
	(0.074)	(0.092)	(0.022)				
C17 paper and pulp products	0.338***	0.290***	0.310***	438	63	0.20	*yes*
	(0.054)	(0.058)	(0.027)				
C18 printing and recorded media	0.206**	0.202***	0.233*	399	65	0.00	*yes*
	(0.098)	(0.052)	(0.134)				
C20 chemicals and chemical products	0.334***	0.240**	0.358***	619	90	0.27	*yes*
	(0.037)	(0.103)	(0.063)				
C21 pharmaceutical products	0.253***	0.030	0.685***	238	32	0.92	*no*
	(0.073)	(0.026)	(0.206)				
C22 rubber and plastics products	0.329***	0.158***	0.530***	1,579	227	0.82	*yes*
	(0.012)	(0.060)	(0.031)				
C23 other non-metallic mineral products	0.305***	0.184**	0.500***	921	123	1.00	*yes*
	(0.116)	(0.075)	(0.193)				
C24 basic metals	0.386	0.197*	0.388**	394	54	1.00	*yes*
	(0.279)	(0.105)	(0.169)				
C25 fabricated metal products	0.508***	0.027***	0.417***	3,191	474	0.00	*yes*
	(0.000)	(0.000)	(0.000)				
C26 computer, electronic, optical products	0.458***	0.011	0.587***	879	115	0.12	*yes*
	(0.020)	(0.007)	(0.013)				
C27 electrical equipment	0.325***	0.094**	0.571***	775	105	0.92	*yes*
	(0.018)	(0.047)	(0.088)				
C28 machinery	0.380***	0.073**	0.511***	1,642	230	0.06	*yes*
	(0.005)	(0.035)	(0.011)				
C29 motor vehicles, trailers, semi-trailers	0.414***	0.133***	0.532***	1,029	136	0.00	*yes*
	(0.003)	(0.016)	(0.021)				
C30 other transport equipment	0.300***	0.077**	0.623***	147	20	1.00	*no*
	(0.025)	(0.032)	(0.046)				
C31 furniture	0.526	0.136*	0.292*	380	55	0.92	*yes*
	(0.333)	(0.081)	(0.168)				
C32 other manufacturing	0.353***	0.092***	0.497***	431	70	0.04	*yes*
	(0.039)	(0.023)	(0.013)				
C33 repair, installation	0.460	0.044	0.706**	336	57	0.71	*yes*
	(0.326)	(0.105)	(0.333)				
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table D.3: Results of production function estimation for Hungary

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.146***	0.038**	0.764***	2,485	399	0.00	*yes*
	(0.006)	(0.019)	(0.010)				
C11 beverages	0.147***	0.122***	0.796***	520	77	0.00	*yes*
	(0.041)	(0.033)	(0.042)				
C13 textiles	0.288***	0.099***	0.510***	510	81	0.00	*yes*
	(0.023)	(0.029)	(0.045)				
C14 wearing apparel	0.387***	0.047*	0.474***	895	148	0.00	*yes*
	(0.012)	(0.028)	(0.016)				
C15 leather	0.447***	0.059	0.476***	363	58	0.68	*yes*
	(0.108)	(0.062)	(0.068)				
C16 wood products	0.101***	0.097**	0.678***	1,757	281	0.00	*yes*
	(0.020)	(0.040)	(0.017)				
C17 paper and pulp products	0.132***	0.149***	0.801***	405	58	0.03	*yes*
	(0.048)	(0.047)	(0.012)				
C18 printing and recorded media	0.152***	0.126***	0.570***	555	80	0.00	*no*
	(0.012)	(0.025)	(0.016)				
C20 chemicals and chemical products	0.165	0.145*	0.627	462	75	0.92	*no*
	(0.150)	(0.075)	(0.484)				
C21 pharmaceutical products	*NA*	*NA*	*NA*	98	13	*NA*	*no*
	NA	*NA*	*NA*				
C22 rubber and plastics products	0.172***	0.039**	0.801***	2,050	298	0.00	*yes*
	(0.012)	(0.016)	(0.006)				
C23 other non-metallic mineral products	0.131***	0.019	0.786***	1,156	171	0.00	*yes*
	(0.010)	(0.037)	(0.020)				
C24 basic metals	0.139***	0.038	0.763***	437	61	0.00	*yes*
	(0.032)	(0.057)	(0.023)				
C25 fabricated metal products	0.209***	0.000	0.575***	5,764	911	0.00	*yes*
	(0.009)	(0.012)	(0.011)				
C26 computer, electronic, optical products	0.200***	−0.041	0.765***	678	107	0.30	*yes*
	(0.046)	(0.054)	(0.047)				
C27 electrical equipment	0.323***	0.056***	0.557***	1,227	177	0.04	*yes*
	(0.017)	(0.018)	(0.013)				
C28 machinery	0.221***	0.077***	0.648***	2,081	306	0.00	*yes*
	(0.006)	(0.020)	(0.009)				
C29 motor vehicles, trailers, semi-trailers	0.241***	0.112***	0.625***	899	139	0.63	*yes*
	(0.021)	(0.032)	(0.017)				
C30 other transport equipment	0.281***	0.006	0.694***	164	23	1.00	*no*
	(0.119)	(0.061)	(0.283)				
C31 furniture	0.158***	0.058**	0.691***	914	135	0.00	*yes*
	(0.011)	(0.025)	(0.012)				
C32 other manufacturing	0.251***	0.063	0.651***	446	67	0.52	*yes*
	(0.028)	(0.070)	(0.023)				
C33 repair, installation	0.361***	0.002	0.534***	1,439	206	0.00	*yes*
	(0.014)	(0.022)	(0.008)				

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables.

*p<0.1; **p<0.05; ***p<0.01

Table D.4: Results of production function estimation for Slovakia

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.294***	0.026	0.679***	1,062	148	1.00	*yes*
	(0.012)	(0.022)	(0.011)				
C11 beverages	0.264***	0.104***	0.709***	120	16	0.35	*no*
	(0.009)	(0.035)	(0.055)				
C13 textiles	0.223***	0.240**	0.452***	336	43	0.15	*no*
	(0.033)	(0.118)	(0.060)				
C14 wearing apparel	2.434***	0.281***	2.127***	211	28	0.00	*yes*
	(0.236)	(0.040)	(0.202)				
C15 leather	0.265***	0.019	0.554***	130	15	0.00	*yes*
	(0.067)	(0.028)	(0.082)				
C16 wood products	0.374	0.021	0.494	1,138	156	0.84	*yes*
	(0.239)	(0.049)	(0.306)				
C17 paper and pulp products	0.199*	0.091	0.683*	308	43	1.00	*yes*
	(0.112)	(0.058)	(0.390)				
C18 printing and recorded media	0.317***	0.087	0.421***	508	67	0.00	*yes*
	(0.019)	(0.062)	(0.065)				
C20 chemicals and chemical products	0.263***	0.051*	0.678***	504	61	0.59	*no*
	(0.011)	(0.026)	(0.014)				
C21 pharmaceutical products	*NA*	*NA*	*NA*	50	6	*NA*	*no*
	NA	*NA*	*NA*				
C22 rubber and plastics products	0.383***	0.073***	0.505***	1,628	219	0.24	*yes*
	(0.010)	(0.007)	(0.018)				
C23 other non-metallic mineral products	0.300***	0.180***	0.478***	604	79	0.53	*yes*
	(0.027)	(0.044)	(0.041)				
C24 basic metals	0.324***	0.070***	0.577***	366	46	0.26	*yes*
	(0.027)	(0.024)	(0.013)				
C25 fabricated metal products	0.498***	0.032	0.377***	3,956	550	0.00	*yes*
	(0.008)	(0.025)	(0.004)				
C26 computer, electronic, optical products	0.297***	0.086***	0.489***	652	81	0.00	*yes*
	(0.012)	(0.022)	(0.024)				
C27 electrical equipment	0.339	0.103	0.508	736	95	1.00	*yes*
	(0.278)	(0.089)	(0.427)				
C28 machinery	0.317***	0.036***	0.602***	1,665	203	0.00	*yes*
	(0.003)	(0.006)	(0.001)				
C29 motor vehicles, trailers, semi-trailers	0.326***	0.012	0.615***	397	54	0.00	*no*
	(0.006)	(0.011)	(0.006)				
C30 other transport equipment	*NA*	*NA*	*NA*	99	15	*NA*	*no*
	NA	*NA*	*NA*				
C31 furniture	0.303***	0.023***	0.554***	716	95	0.00	*yes*
	(0.009)	(0.001)	(0.016)				
C32 other manufacturing	0.422***	0.036*	0.429***	332	42	0.19	*no*
	(0.041)	(0.018)	(0.043)				
C33 repair, installation	0.608***	−0.044	0.324***	671	111	0.00	*yes*
	(0.046)	(0.072)	(0.050)				

Note: All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables.

*p<0.1; **p<0.05; ***p<0.01

Table D.5: Results of production function estimation for Slovenia

I want a quiet Life! On Productivity and Competition in the Central European Energy Sector

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Abstract: An important proposition in Economics claims that competition spurs technical efficiency, as it forces firms to raise competitiveness to survive market pressure. This study examines the effects of firm-level Lerner indexes on productivity, using a dataset on energy firms from Central European post-communist countries during 2009-2017. The energy sector is of particular interest, as markets are still concentrated, although governments have liberalised them considerably. To contribute to the literature, I derive Lerner indexes from the production function next to involving the return on sales. Supporting the literature, the overall results highlight that market power significantly decreases productivity.

JEL: L11, L25, L51, Q40, Q48

Keywords: Concentration, Productivity, Regulation, Energy Markets, Energy Reform

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1 Introduction

In previous decades, EU member states liberalised energy sectors (e.g. unbundling, elimination of entry barriers etc.) and privatised public companies to establish competition between energy suppliers. [1] Despite the market restructuring, many segments including generation are still highly concentrated. [2] In comparison to energy generation, transmission and distribution are heavily regulated, since these segments suffer from natural monopolies due to high sunk costs of constructing grids (Meletiou *et al.* (2018), Ajayi *et al.* (2017), Armstrong & Sappington (2007)).

A long-held proposition is that competition spurs firm-level productivity (Orazem & Vodopivec (2009)). Therefore, the natural question arises how market concentration and liberalisation policies affect productivity of firms. Economic theory, however, provides conflicting guidance. First, standard oligopoly models conclude that competitive pressures force firms to produce efficiently, i.e.: competitive pressures are the strongest in Bertrand models with homogenous products, but become weaker in the same model with heterogenous goods and the Cournot model (Hay & Liu (1997)). Second, Leibenstein (1966) argues that fiercer competition decreases technical inefficiency. Competitive pressure reduces managerial slack by pushing managers to spend more effort on avoiding the firm going bankrupt. Competition also improves stockholders' ability to assess corporate performance. Similarly, the *Quiet Life* hypothesis (QL) claims that market power allows managers to reduce efforts dropping technical efficiency (Hicks (1935)). For instance, market concentration enables managers to charge prices above marginal costs eliminating incentives to keep costs under control. Market power allows the management to pursue goals other than profit maximisation (principal-agent problem). Moreover, market power facilitates rent-seeking, i.e.: firms allocate funds to obtain, maintain and expand market power. Additionally, less market pressure supports incompetent managers to keep their positions (Alshammari *et al.* (2019), Berger & Hannan (1998)). Fourth, the *Structure Conduct Performance* hypothesis (SCP) developed by Bain (1956) suggests that smaller numbers of firms in markets characterised by strong market barriers may ease collusion. Hence, firms benefit from more market power, higher prices and profitability. Fifth, the *Efficient Structure* hypothesis (ES) by Demsetz (1973) proposes a positive link between market concentration and profitability. Higher productivity helps firms to lower prices, resulting in higher market shares and concentration, and obtain higher profits. Given the lower prices, consumers also benefit. Last, the *Relative Market Power* hypothesis (RMP) proposes that higher market shares imply more market power and, finally, higher firm-level profits (Shepherd (1986), Shepherd (1983)). In comparison, consumers lose rents, since firms raise prices and reap profits (Berger & Hannan (1998), Berger (1995)).

A number of studies analyses the impacts of regulatory reforms on technical efficiency of energy firms, mostly employing cost function estimation. At the firm level, Gugler *et al.* (2017), Triebs *et al.* (2016), Filippini & Wetzel (2014), Gao & Van Biesebroeck (2014), Fetz & Filip-

[1]For instance, see `https://stats.oecd.org/Index.aspx?DataSetCode=ETCR` or `https://stats.oecd.org/Index.aspx?DataSetCode=SECTREG2018`

[2]This finding can be observed from the market shares of the largest electricity generators, downloadable from Eurostat (`https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_ind_331a&lang=en`).

pini (2010), Rungsuriyawiboon & Stefanou (2007), Fraquelli *et al.* (2005), Piacenza & Vannoni (2004), Kwoka (2002), Kleit & Terrell (2001), Considine (2000), Hayashi *et al.* (1997), Kaserman & Mayo (1991), and Nelson & Wohar (1983) explore the effects of regulatory reforms, primarily deregulation and vertical disintegration, on the cost efficiency of electricity generators, transmission and distribution system operators.
Another strand of the literature investigates the relationship between markups and international trade, such as the papers by Lu & Yu (2015), De Loecker & Goldberg (2014), De Loecker & Warzynski (2012), Krishna & Mitra (1998), Harrison (1994), Levinsohn (1993).
Concerning the relationship between competition and technical efficiency, most studies examine banking, insurance, hospital, manufacturing and transportation industries. Bajtelsmit & Bouzouita (1998) support the SCP hypothesis. Choi & Weiss (2005) favor the ES hypothesis. Evidence giving rise to the QL hypothesis is found by the majority of studies (e.g. Alshammari *et al.* (2019), Castelnovo *et al.* (2019), Alhassan & Biepke (2016), Bougna & Crozet (2016), Daveri *et al.* (2016), Schivardi & Viviano (2011), Griffith *et al.* (2010), Chi-Lok & Zhang (2009), Orazem & Vodopivec (2009), Fenn *et al.* (2008), Okada (2005), Tang & Wang (2005), Syverson (2004), Disney *et al.* (2003), Blundell *et al.* (1999), Berger & Hannan (1998), Dalmau-Matarrodona & Puig-Junoy (1998), Hay & Liu (1997) and Nickell (1996)), but it is rejected by Bayeh *et al.* (2021) and Maudos & de Guevara (2007). Last, Weiss & Choi (2008) obtain mixed results, while Atayde *et al.* (2021) do not find significant effects of competition on productivity. Next to the literature investigating the relationship between productivity and competition, Aghion *et al.* (2005), Aghion *et al.* (2008) and Inui *et al.* (2012) relate productivity growth to Lerner indexes. While the first and third paper find a concave relationship, the second one observes a convex one. This study combines the approaches of many other studies and, therefore, adds to the literature in several aspects. First, this work is one of the few investigating the effects of competition on energy firms' productivity. In comparison, the vast majority of studies examines the effects on cost efficiency or efficiency obtained by DEA. Therefore, it fills this void of lacking empirical evidence. Second, this study employs the framework proposed by De Loecker & Warzynski (2012) for measuring Lerner indexes, and it has the advantage of introducing them next to the conventional return on sales definition.

Motivated by this aspect, the following article explores the effects of firm-level Lerner indexes on productivity. Therefore, micro-data on energy firms (D35) from Czech Republic, Hungary and Slovakia during 2009-2017 are employed. The core business of relevant firms primarily covers energy generation (e.g. electricity, gas, steam and air conditioning) and their distribution. The energy industry is of special interest for two reasons. First, although governments have eliminated market barriers by vertically disintegrating generation and grids, markets are still concentrated. Second, many companies in network industries are publicly owned. Post-communist countries are particularly interesting due to their history. Analysed countries transitioned from planned to market economies after the collapse of the Soviet Union experiencing major institutional changes and liberalisations, although the government's influence in these countries is still pervasive. Especially post-communist countries are characterised by strong entry barriers aggravating the transition to well-functioning market economies. Furthermore, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies strengthening

market barriers (Buccirossi & Ciari (2018)). Furthermore, the three countries do not only belong to the Continental Central-East region, but are also members of the Visegrad group, the longest and most developed and important regional cooperation within Central Europe. National network industries are highly interlinked with each other, but also with their Western neighbours (e.g. Austria, Germany) (CEEP (2018)). Given theory and empirical findings, I hypothesise that higher market power decreases technical efficiency in these industries.
I apply a two-staged framework. In the first stage, I estimate translog production functions applying the algorithm by Ackerberg *et al.* (2015) to obtain technical efficiency. In the second-stage, I regress productivity on Lerner indexes employing system GMM to consider endogeneity. Generally, the results show that market power significantly drops productivity supporting the models suggesting a positive effect of competitive pressure on productivity. Hence, governments should foster liberalisation and eliminate further market barriers. Furthermore, larger firms operate less efficiently implying that firms suffer from incomplete structural reforms and misallocations during the Soviet era.

The paper proceeds as follows. *Section 2* briefly introduces this work's empirical framework and data, used to examine the impacts of firm-level Lerner indexes on productivity, while *Section 3* provides the results of the estimations of the production function and discusses the estimated effects of market power on technical efficiency. Last, *Section 4* sums up and draws conclusions.

2 Empirical strategy and data

This section describes the empirical strategy consisting of two stages. In the first stage, I estimate production functions allowing to obtain firm-level productivity. In the second stage, I regress productivity on Lerner indexes to establish a link between competitive pressure and technical efficiency.

2.1 First stage: estimation of the production function

I follow the literature (e.g. Gemmell *et al.* (2018), Richter & Schiersch (2017), Collard-Wexler & De Loecker (2015), Lu & Yu (2015), Du *et al.* (2014), Del Bo (2013), Doraszelski & Jaumandreu (2013), Crinò & Epifani (2012), De Loecker & Warzynski (2012), Arnold *et al.* (2011), De Loecker (2007a), Javorcik (2004)) and consider a three-input revenue-based second-order translog production function, as described in equation (1). y denotes logged revenue (dependent variable), k logged capital (state variable), l logged labour (free variable), and m logged material. ζ is the sum of unobserved productivity ω and the measurement error of the productivity shock ψ. The indices i and t represent firms and years. Although Cobb-Douglas production functions are probably the most popular function type, I choose a translog specification, because it is more flexible, though data demanding (Syverson (2011)). The polynomial involves all logged inputs, their squares, and all their interaction terms (De Loecker & Warzynski (2012)).

$$\begin{aligned} y_{i,t} =& \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + \\ & \beta_{kk} \cdot k_{i,t}^2 + \beta_{ll} \cdot l_{i,t}^2 + \beta_{mm} \cdot m_{i,t}^2 + \\ & \beta_{kl} \cdot k_{i,t} \cdot l_{i,t} + \beta_{km} \cdot k_{i,t} \cdot m_{i,t} + \\ & \beta_{lm} \cdot l_{i,t} \cdot m_{i,t} + \underbrace{\omega_{i,t} + \psi_{i,t}}_{\zeta_{i,t}} \end{aligned} \tag{1}$$

For any given firm i, in any given year t, output elasticities of the variables are calculated by taking the first-order derivatives as given by equation (2).

$$\begin{aligned} \frac{\partial y_{i,t}}{\partial k_{i,t}} &= \beta_k + 2 \cdot \beta_{kk} \cdot k_{i,t} + \beta_{kl} \cdot l_{i,t} + \beta_{km} \cdot m_{i,t} \\ \frac{\partial y_{i,t}}{\partial l_{i,t}} &= \beta_l + 2 \cdot \beta_{ll} \cdot l_{i,t} + \beta_{kl} \cdot k_{i,t} + \beta_{lm} \cdot m_{i,t} \\ \frac{\partial y_{i,t}}{\partial m_{i,t}} &= \beta_m + 2 \cdot \beta_{mm} \cdot m_{i,t} + \beta_{km} \cdot k_{i,t} + \beta_{lm} \cdot l_{i,t} \end{aligned} \tag{2}$$

I estimate the production function applying the method by Ackerberg *et al.* (2015), using l as free variable, k as state variable and m as proxy variable (Garcia-Marin & Voigtländer (2019), Richter & Schiersch (2017), Collard-Wexler & De Loecker (2015), Lu & Yu (2015), De Loecker & Warzynski (2012), Higón & Antolín (2012)). A brief explanation of the algorithm is provided in appendix E. To allow for heterogenous input elasticities β across country levels, I follow the literature (e.g. Fons-Rosen *et al.* (2021), Gemmell *et al.* (2018), Levine & Warusawitharana (2021), Olper *et al.* (2016)) and estimate equation (1) for each country pooling observations across two-digit NACE industries. After estimating the production function, derived input elasticities are used to construct logged total factor productivity $log(TFP)$ for each sampled firm i and year t, as shown in equation (3). As productivity is the residual, it quantifies the changes in output while keeping inputs constant. Owing to the logged dependent variable, productivity is also logged (Javorcik (2004), Olley & Pakes (1996)).

$$\begin{aligned} log(TFP_{i,t}) =& y_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \\ & - \beta_{kk} \cdot k_{i,t}^2 - \beta_{ll} \cdot l_{i,t}^2 - \beta_{mm} \cdot m_{i,t}^2 \\ & - \beta_{kl} \cdot k_{i,t} \cdot l_{i,t} - \beta_{km} \cdot k_{i,t} \cdot m_{i,t} - \beta_{lm} \cdot l_{i,t} \cdot m_{i,t} \end{aligned} \tag{3}$$

2.1.1 Data

Firm-level data is downloaded from the Orbis database. Orbis, published by Bureau van Dijk, provides accounting data, legal form, industry activity codes, and incorporation date for a large set of private and public firms worldwide. I include medium sized, large and very large [3]; active and inactive companies from sector D ('electricity, gas, steam and air conditioning', e.g.: electricity generation, transmission etc., gas production and transmission etc.), incorporated in the Czech Republic, Hungary and Slovakia. The final sample is a nine-year unbalanced panel dataset, from 2009 to 2017. It contains 869 firms with 5,388 observations. [4] [5]

Since product-level output and input quantities are usually not available, while monetary outputs and inputs are only available as firm-level aggregates, I follow the literature and estimate the production function based on producers' real total monetary operating revenues, capital and material expenditures.
Output is defined as real operating revenues. They cover net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk (2007)) and are deflated by annual producer price indices, downloaded from the Eurostat database [6], that vary across countries, two-digit NACE industries and years. To calculate real tangible fixed assets (e.g.: machinery), tangible fixed assets are deflated by an uniform investment good price index, sourced from the OECD database [7], varying across countries and years. Next, labour is a physical quantity measuring the total number of employees included in the company's payroll. Last, real material expenditures, approximating material, are the material costs, defined as the sum of expenditures on raw materials and intermediate goods, deflated by an uniform intermediate good price index. It is sourced from the same database and varies at the same level (Castelnovo *et al.* (2019), Richter & Schiersch (2017), Du *et al.* (2014), Nishitani *et al.* (2014), Baghdasaryan & la Cour (2013), Del Bo (2013), Crinò & Epifani (2012), Higón & Antolín (2012), Javorcik (2004)). [7]

However, one set of econometric issues results from employing deflated monetary values of inputs instead of quantities. Potential differences in input prices across firms, implied by differences in the access to input markets or monopsony positions, might cause the 'input price bias'. When ignoring this issue, the framework implicitly assumes that all firms face identical input prices. Hence, derived estimates would suffer from input price biases, in case of input price differences. Resulting coefficients are biased downwards, while constructed productivity, finally, is biased upwards. In this work, I only rely on two deflated monetary inputs, capital and material, potentially causing biased coefficients, while labour is measured physically (De Loecker & Goldberg (2014)). Furthermore, Gandhi *et al.* (2020) show that material demand may not

[3] Orbis considers firms to be 'medium sized', when operating revenues $\geq$ 1 mio EUR or total assets $\geq$ 2 mio EUR or employees $\geq$ 15. Orbis defines firms to be 'large', when operating revenues $\geq$ 10 mio EUR or total assets $\geq$ 20 mio EUR or employees $\geq$ 150. Firms are 'very large', when operating revenues $\geq$ 100 mio EUR or total assets $\geq$ 200 mio EUR or employees $\geq$ 1,000 or the company is listed (Bureau van Dijk (2007)).

[4] As data on Slovakia 2017 were only barely available in Orbis, I exclude the few available observations.

[5] Observations with implausible output and input values (e.g. negative values) or missing values are dropped. Firms with either unknown or unavailable activity status are eliminated.

[6] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sts_inpp_a&lang=de`

[7] `https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI`

completely reflect productivity complicating the identification of revenue-based production functions. To tackle these problems, I follow the literature (e.g. Doraszelski & Jaumandreu (2021), Gandhi *et al.* (2020), Garcia-Marin & Voigtländer (2019), Doraszelski & Jaumandreu (2018), Lu & Yu (2015), Doraszelski & Jaumandreu (2013), De Loecker & Warzynski (2012)) and introduce a demand shifter a. Usually, these papers involve firm-level lagged real input prices, exports etc. Like Doraszelski & Jaumandreu (2021), Gandhi *et al.* (2020), Doraszelski & Jaumandreu (2018), Doraszelski & Jaumandreu (2013) I include the lagged input price of labour, the lagged average real wage per worker. [8] It does not enter the production function as an input, but affects the demand for material and, therefore, is part of the polynomial used to proxy for unobserved productivity. In other words, omitted firm-level input prices are assumed to be a reduced-form function of the demand shifter which is interacted with deflated inputs (Gandhi *et al.* (2020), Doraszelski & Jaumandreu (2018), Lu & Yu (2015), De Loecker & Warzynski (2012)). Given the lag, every firm's first observation will be dropped. Data on firm-level wage costs are sourced from Orbis as well, which are deflated by national consumer price indices, downloaded from Eurostat [9], and divided by firm-level employment. [10] Alternatively, some studies (e.g. Raval (2020)) suggest to calculate the production function's coefficients non-parametrically as the shares of input costs in output assuming a Cobb-Douglas production function with constant returns to scale. Relevant methods might be applicable to manufacturing sectors, while network industries usually benefit from increasing returns to scale violating the assumption of constant returns to scale.

Next, a further set of econometric issues is implied applying deflated monetary values of output instead of quantities ('output price bias'). Although firm-level or even product-level price indices would be necessary, they are usually not available. Price indices, however, are only available at some industry-level. Applying industry-level price indices to firm-level operating revenues causes biased coefficients of the production function, if firm- or product-level prices deviate from the development of the industry-level price index, which are captured by the error term. The direction of each coefficient's bias is not straightforward and can go in either direction (De Loecker (2007b), De Loecker & Goldberg (2014), Klette & Griliches (1996)). To solve this problem, in the spirit of Klette & Griliches (1996), De Loecker (2007b) proposes a framework, based on including industry-specific aggregate demand shifters, which, however, fails to correctly identify the coefficients, because multiplying all asymmetrically biased input coefficients with a constant cannot yield unbiased input coefficients (Ornaghi (2006)). Consequently, the first stage estimates will suffer from output price biases. Nonetheless, my goal is not to obtain consistent estimates in the first stage as in De Loecker & Warzynski (2012), since they will not affect the second stage results as explained in the following section.

[8] Doraszelski & Jaumandreu (2018) also show that the real price of labour is more relevant than the real price of material. Besides, as fossil fuels, the primary material inputs, are traded at the stock exchange, only little variation across firms is expected. Hence, average real wages are the preferred choice.

[9] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de`

[10] Lu & Yu (2015) also include the firms' market shares as demand shifters. Since data are not available, they can be approximated by dividing firm-level real operating revenues by the country-three-digit NACE industry-specific sums of the same variable. Although such a proxy will suffer from weak precision, results of the first and second stage are robust.

2.2 Second stage: estimation of productivity

To examine the effects of competition on productivity, I regress logged productivity $log(TFP)$ on Lerner indexes LI, control variables X, unobserved company-specific heterogeneity α_i, and nested country-three-digit NACE industry-year dummies $D_c \cdot D_s \cdot D_t$, as described in equation (4). The indices i and t denote firms and years, c the countries, and s the three-digit NACE industries.

$$\begin{aligned} log(TFP_{i,t}) = & \phi \cdot log(TFP_{i,t-1}) + \delta \cdot LI_{i,t} + \beta \cdot size_{i,t} \\ & + \alpha_i + \sum_{c=1}^{C} \sum_{s=1}^{S} \sum_{t=2011}^{2017} \gamma_{c,s,t} \cdot D_c \cdot D_s \cdot D_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

I employ two measures to estimate the effects of concentration. The first one is the return on sales, being the share of variable profits in revenues (Bayeh *et al.* (2021), Atayde *et al.* (2021), Daveri *et al.* (2016), Inui *et al.* (2012), Aghion *et al.* (2008)). As the dataset does not contain data on profits, I define profits as the difference between real operating revenues and the sum of real material costs and wage expenditures following Aghion *et al.* (2008) which simplifies to one minus the shares of real wages and real material costs in real operating revenues. Although this measure does not include capital costs (e.g. interest costs), as they are mostly missing, Aghion *et al.* (2008) show that deducting capital costs barely changes the results. As the second measure, I apply the Lerner indexes obtained by the algorithm by De Loecker & Warzynski (2012) as explained in appendix F. Given the firm's optimisation problem, firm-level price-cost ratios are derived directly from the production function by dividing the marginal effect of the input free of adjustment costs by its share of expenditures in operating revenues. The expenditure share is adjusted by variations in output unrelated to fluctuations in input demand. Resulting price-cost ratios are then transformed to compute Lerner indexes. Following the majority of studies (e.g. Lu & Yu (2015), De Loecker & Warzynski (2012)), I use material as the input free of adjustment costs. In contrast to labour, material is more flexible and less prone to adjustment costs, i.e.: hiring and firing is costly, while adjusting material stocks is simpler given the advanced inventory management (De Loecker & Warzynski (2012)). Moreover, the algorithm by Ackerberg *et al.* (2015) supports picking material. It assumes that labour is chosen prior to other flexible inputs, or is dynamic and subject to adjustment costs. On the other hand, the choice of the variable free of adjustments is crucial, as pointed out by some studies (e.g. Doraszelski & Jaumandreu (2021), Raval (2020)), since results depend on the variable chosen. [11] [12]

[11] As pointed out in *Section* 2.1.1, Raval (2020) suggests to calculate the production function's coefficients non-parametrically as the shares of input costs in revenues assuming a Cobb-Douglas production function with constant returns to scale. Nevertheless, the assumption of constant returns to scale may be too restricitive for energy sectors.

[12] Doraszelski & Jaumandreu (2021) calculate markups from the production function by picking both, material and labour, as inputs free of adjustment costs. As a sensitivity check, I do the same defining the price-cost ratio as the sum of marginal effects over the sum of material and wage expenditures in operating revenues, which is adjusted by variations in output unrelated to fluctuations in input demand. Overall, the results do not respond sensitively to this issue.

For both specifications, only observations with $LI \in [0,1]$ are included, as Lerner indexes lying outside the interval imply either that prices do not cover marginal costs, some products of multi-product firms are complements, or that marginal costs are negative (Tirole (1994)). In other words, observations with Lerner indexes lying outside the interval do not provide information on the degree of market power and, therefore, would bias results and turn them meaningless. [13] Negative values, for instance, result either from losses or, for the case of the second measure, from corrected shares of material expenditures in operating substantially exceeding the estimated marginal effect of material. Excluding relevant observations is relevant, as firms with negative Lerner indexes also suffer from low productivity implying upwards biased coefficients.

Following Castelnovo *et al.* (2019) and Del Bo (2013), I involve the firm's logged real total assets to capture the effects of firm size $size$. Given the literature, their effect is ambiguous, as empirical works find both, positive and negative, impacts (e.g. Castelnovo *et al.* (2019), De & Nagaraj (2014), Del Bo (2013), Ye *et al.* (2012), Diaz & Sanchez (2008), Yasuda (2005), Haltiwanger *et al.* (1999), Berger & Hannan (1998), Majumdar (1997)). On the one hand, larger companies benefit from economies of scale. On the other hand, larger firms might suffer from organizational and agency problems. Besides, the Soviets have excessively supported larger firms by misallocating resources (Buccirossi & Ciari (2018), De Rosa *et al.* (2015)). Furthermore, constructing new plants is costly due to the high fixed costs.

The specification involves firm-level fixed effects α_i, controlling for unobserved firm-specific heterogeneity (country, legal form, price regulation scheme). Last, I introduce nested country-three-digit NACE industry-year dummies $D_c \cdot D_s \cdot D_t$, capturing business cycles, institutional quality, European policies, accounting standards, common regulation schemes (e.g. extent of vertical disintegration, regulatory stringency) etc.

One way to estimate equation (4) is OLS. OLS, however, will suffer from inconsistent coefficients. First, Lerner indexes and firm size will be endogenous to productivity due to simultaneities. Plausibly, higher efficiency decreases marginal costs allowing firms to charge lower prices. Finally, lower prices result in higher market shares and, thus, more market power (Bayeh *et al.* (2021), Daveri *et al.* (2016), Demsetz (1973)). Similarly, endogeneity of real total assets also arises due to simultaneity, as higher efficiency provides more funds to expand. Second, measurement errors imply inconsistent coefficients. Since the first stage estimates suffer from output price biases, both, the dependent variable and the variable of interest, include measurement errors.

A common solution to these issues is the application of instrumental variables. Therefore, I employ the two-step system GMM method by Blundell & Bond (1998), frequently used in the literature analysing energy industries (e.g. Bayeh *et al.* (2021), Pereira da Silva & Cerqueira (2017), Growitsch & Stronzik (2014), Fiorio & Florio (2013), Gugler *et al.* (2013)). In previous years, difference and system GMM were increasingly popular in the literature. Both methods, designed for panels with a large number of observations and few time periods, aim to solve situ-

[13] When using return on sales, 321 out of 4,329 observations that can be employed in the first stage drop. When applying the Lerner indexes calculated from the production function, 341 observations lie outside the relevant interval.

ations with endogenous and predetermined variables, fixed effects, autocorrelation within firms, heteroskedasticity, dynamic dependent variables, and the only available instruments being 'internal' (lags of the instrumented variables). In comparison to the first, the latter has better finite sample properties concerning bias and root mean squared error (Roodman (2009b)).

In my case, system GMM addresses the endogeneity concerns that would turn OLS estimates biased. To obtain consistent coefficients, system GMM regression exploits the property that lagged variables will serve as strong instruments for their current values given serial correlation and, therefore, estimates a two-equation system. First, similar to difference GMM, equation (4) is regressed in first differences eliminating firm-specific heterogeneity. The first differences are instrumented with the lagged variables' levels. Second, equation (4) is estimated in levels instrumenting them with their first differences. The introduction of the second equation allows more instruments and may substantially raise efficiency (Roodman (2009b)). Instrumenting first differences in the lagged levels in difference equation, and levels with the first differences in the level equation does not only solve endogeneity stemming from simultaneities, but also deals with measurement errors. Permanent measurement errors will be absorbed by the firm-level fixed effects. Temporary measurement errors, however, only bias the coefficient of the lagged dependent variable, while the coefficients of the explanatory variables are consistently estimated. Therefore, temporary measurement errors are required to be serially uncorrelated (Bond *et al.* (2001)). An analogous assumption is imposed by the algorithm by De Loecker & Warzynski (2012) ruling out dynamics in pricing. Electricity and gas are quite homogeneous and traded on the stock exchanges. Hence, prices are usually volatile. The analogous holds for steam and air conditioning whose major inputs, fossil fuels, are traded on stock exchanges implying volatile output prices. Besides, measurement errors must be uncorrelated with past idiosyncratic productivity shocks. Given the high volatility of energy prices, this assumption is likely to be satisfied as well (Bond *et al.* (2001)).

Applying system GMM requires variables to be classified either as endogenous, predetermined or exogenous variables. Following the literature, I consider Lerner indexes as endogenous variables. In comparison, I define the lagged dependent variable as predetermined variable, being variables that do not correlate with contemporaneous errors but with past ones, $\epsilon_{i,t-1}$ (Pereira da Silva & Cerqueira (2017), Roodman (2009b)). Logged real total assets are also involved as predetermined variable due to the long construction times of utilities. Last, I introduce nested year dummies as strictly exogenous variables.
I employ two-step estimators. While they are more efficient than one-step estimators, they suffer from downwards biased standard errors (Roodman (2009b)). These are corrected by the Windmeijer (2005) method. The inclusion of one lag in the dependent variable suffices to achieve serially uncorrelated levels of errors [14] in equation (4), similar to other studies (e.g. Pereira da Silva & Cerqueira (2017), Growitsch & Stronzik (2014), Fiorio & Florio (2013), Gugler *et al.* (2013)). Owing to the introduction of the demand shifter in the first stage, every firm's first observation drops. This approach, however, implies that each firm's second observation and,

[14] This condition is satisfied, if the first differences of the errors are negatively correlated of order one and are uncorrelated of higher orders (Roodman (2009b)).

therefore, observations of the second year are also dropped.

3 Results

In the first step of the analysis, I estimate the production function for each country. Summary statistics are displayed in the first block of *Table* 1. The second block shows the same for the regressions examining the effects of Lerner indexes. Besides, the table also illustrates the high coverage of smaller firms (e.g. that only have few employees).

Variable	Unit	Mean (SD)	Min - Med - Max	IQR
First Stage				
Real Operating Revenues	Tsd. Euro	62,977.6 (311,856.4)	0.0 < 3,308.3 < 6,629,959.0	12,665.5
Real Tangible Fixed Assets	Tsd. Euro	40,030.9 (238,528.4)	0.1 < 3,090.5 < 4,928,768.0	9,030.3
Number of Employees	Integer	83.8 (217.4)	1.0 < 23.0 < 2,750.0	68.0
Real Material Costs	Tsd. Euro	44,428.9 (279,491.5)	0.0 < 1,706.5 < 7,827,705.0	7,633.6
Average Real Wage	Tsd. Euro	21.3 (37.0)	0.0 < 16.1 < 1,696.4	11.8
Second Stage				
$log(TFP)$		11.6 (4.3)	-3.1 < 12.1 < 24.9	4.7
Lerner Index (ROS)	Percent	0.4 (0.3)	0.0 < 0.3 < 1.0	0.4
Lerner Index (Productivity)	Percent	0.4 (0.2)	0.0 < 0.4 < 1.0	0.3
Real Total Assets	Tsd. Euro	43,903.3 (246,424.8)	0.0 < 3,415.1 < 4,941,011.0	9,682.9
ISO_{CZ}	Binary	0.6 (0.5)	0.0 < 1.0 < 1.0	1.0
ISO_{HU}	Binary	0.2 (0.4)	0.0 < 0.0 < 1.0	0.0
ISO_{SK}	Binary	0.2 (0.4)	0.0 < 0.0 < 1.0	0.0
$NACE_{electricity, gas}$	Binary	0.5 (0.5)	0.0 < 1.0 < 1.0	1.0
$NACE_{steam, air}$	Binary	0.5 (0.5)	0.0 < 0.0 < 1.0	1.0
Legal Form $_{public limited}$	Binary	0.3 (0.5)	0.0 < 0.0 < 1.0	1.0
Legal Form $_{private limited}$	Binary	0.7 (0.5)	0.0 < 1.0 < 1.0	1.0
Regulatory Quality	Continuous	1.0 (0.2)	0.6 < 1.0 < 1.3	0.2
Note:	'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, and 'IQR' the interquartile range. Some values (e.g. inputs, Lerner indexes) are shown to be zero given the rounding. Note that $log(TFP)$ and its level cannot be interpreted in a meaningful way.			

Table 1: Descriptive statistics

3.1 Results of the first stage

I perform the analysis as outlined in *Section* 2 and estimate the translog production function for each country. For each input, it follows a distribution of firm-level input elasticities of output that are obtained the way as shown in equation (2). *Table* 2 summarizes the expected values of the input elasticities. The columns display the elasticities of each input by countries, while the rows of the first block show the elasticities of each input. The rows of the second block provide the sum of elasticities, the third block the numbers of observations and firms.

Owing to the log-log representation, the expected partial effects are interpreted as elasticities, i.e.: in column (1), the capital elasticity of output equals 0.264, meaning that output rises on average by 0.264%, when capital increases by 1%, keeping everything else constant.

Results, though being heterogeneous, are consistent with the literature (e.g. Richter & Schiersch (2017), Lu & Yu (2015), Du *et al.* (2014), Arnold *et al.* (2011)). Labour elasticities vary between 0.20 and 0.40 (Richter & Schiersch (2017), Arnold *et al.* (2011)). Mentioned studies analysing manufacturing sectors obtain capital elasticities lying between 0 and 0.10. In Lu & Yu (2015), however, they are higher resembling mine. Plausibly, marginal effects of capital are higher in energy sectors, since they produce more capital-intensively. Depending on the study, material elasticities vary between 0.40 and 0.90, confirming my results as well. As can be concluded from the sum of the expected values of the elasticities, increasing returns to scale are observed in every country, supporting the hypothesis that energy industries, on average, are still benefiting from natural monopolies.

The first drawback of the given specification might be that marginal effects may differ across firm size. However, given the high flexibility of the translog function (e.g. marginal effects vary across firms and years), this issue might be minor. Particularly, when calculating averages across company categories used to filter observations in Orbis ('medium sized', 'large', 'very large'), larger firms benefit more strongly from increasing returns to scale than smaller firms do. While average effects of capital and labour stay constant across size categories, the average elasticity of material rises with firm size. Second, production functions vary across industries. In comparison, only few studies (e.g. Commins *et al.* (2011)) allow for heterogeneous effects across industries by pooling observations across countries. When following this approach, results, however, are similar. Given the small number of gas firms, they are included in the electricity firms. [15]

	Country		
	Czech Republic (1)	Hungary (2)	Slovakia (3)
Capital	0.264	0.167	0.169
	(0.009)	(0.008)	(0.005)
Labour	0.333	0.440	0.240
	(0.007)	(0.022)	(0.006)
Material	0.648	0.822	0.903
	(0.017)	(0.025)	(0.016)
Sum of Elasticities	1.245	1.429	1.312
	(0.016)	(0.026)	(0.017)
Number of Observations	2,425	839	1,065
Number of Firms	445	142	188
Note:	For each country, expected input elasticities and their sums are cluster bootstrapped using 1000 Bootstrap repetitions. The size of the drawn subsamples coincides with the referring country's number of observations. Derived standard deviations are provided in parenthesis.		

Table 2: Expected input elasticities of output of the translog production function

Figure 1 displays average Lerner indexes by three-digit NACE industries. Given the small size of the gas industry, it is assigned to the electricity industry, as both were liberalised in previous decades. Average return on sales-style Lerner indexes are illustrated by the solid lines, while Lerner indexes obtained from the production functions are shown by the dashed lines. Concerning the latter, the first observations drop given the inclusion of the lagged demand shifter. On average, Lerner indexes are higher in the electricity and gas industry (D351, D352) that are both subject to incentive regulation spurring firms to produce more efficiently. In comparison,

[15]In the electricity and gas industry, the expected values of the marginal effects of capital, labour and material are 0.240, 0.407 and 0.635. In the steam and air conditioning industry, the same expected values equal 0.094, 0.376 and 0.915.

average Lerner indexes are smaller in the steam and air conditioning industry (D353) which is characterised by high sunk costs to construct and maintain local grids. All average Lerner indexes evolve quite stable over time. While in the electricity and gas industries Lerner indexes derived by the different methods follow similar trends, the correlation for the steam and air conditioning industry is weaker. [16] The reason for deviations is the correction of the share of material expenditures when calculating Lerner indexes from the production function. Fluctuations in output unrelated to variations in inputs are excluded, while are completely reflected by the return on sales.

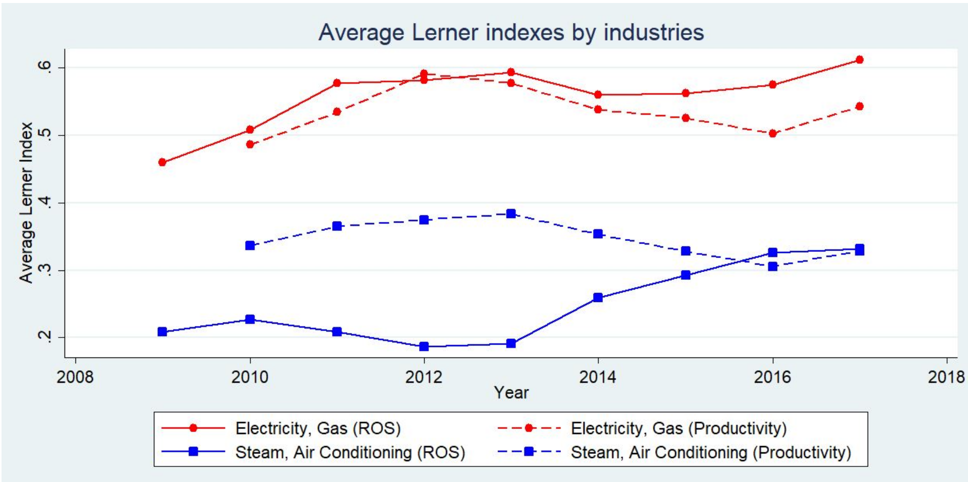

Figure 1: Average Lerner indexes by three-digit NACE industries

Figure 2 provides the average productivity growth rates by the same groups of industries. To obtain percentage points, underlying firm-level growth rates are calculated as the annual differences in $log(TFP)$ and multiplied by 100. On average, productivity grows more strongly in the electricity and gas industries with average growth rates between one and 12 percentage points. In comparison, the steam and air conditioning industry recovered later from the financial crises.

3.2 Results of the second stage

Table 3 shows the results of the two-step GMM regressions of equation (4) taking account of endogeneity. The dependent variable is firm-level $log(TFP)$ in all the regressions. Including only one lag of the dependent variable suffices to obtain serially uncorrelated levels of residuals. More formally, the first differences of the residuals are significantly negatively correlated of order one and uncorrelated of higher orders, as can be seen from the Arellano-Bond tests below the number of instruments. Besides, all the Hansen tests are insignificant, suggesting that all instruments are exogenous and, therefore, the models are correctly specified.
Columns (1) and (2) show the results of the regressions involving the return on sales-style Lerner indexes, while columns (3) and (4) provide the analogous of the regressions introducing the Lerner

[16] Particularly, in the electricity and gas industry the correlation of firm-level Lerner indexes equals 0.77, being highly significant, while in steam and air conditioning industry the correlation coefficient is, though being highly significant too, 0.47

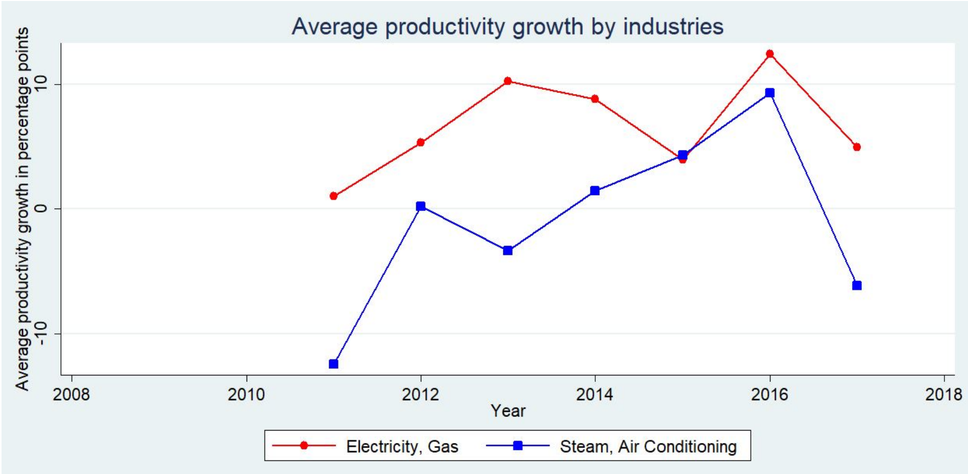

Figure 2: Average productivity growth by three-digit NACE industries

indexes obtained from the production functions. Columns (1) and (3) display the outcomes of the simple regressions, while columns (2) and (4) summarize the results of regressions adding squared Lerner indexes.

In the columns (1) and (3), Lerner indexes significantly decrease productivity supporting the literature. Productivity declines significantly by 1.394-2.325%, if the Lerner index rises by one percentage point. Magnitudes are in line with the literature (e.g. Alshammari *et al.* (2019), Daveri *et al.* (2016), Orazem & Vodopivec (2009), Hay & Liu (1997)). In comparison, columns (2) and (4) suggest concave relationships between productivity and Lerner indexes, implying that marginal effects generally decrease with the size of relevant Lerner indexes. In other words, slack and its negative effect on productivity become more severe with rising market power. Plausibly, when market pressures are still high, productivity losses due to slack and rent-seeking will not be large. Besides, higher market power allows firms to spend more on rent-seeking and provides weaker incentives to keep costs under control resulting in larger efficiency losses. In column (2), the productivity maximising Lerner indexes lies outside the support, while in column (4), the same value is around 0.12. If Lerner indexes increase by one percentage point, starting from the relevant averages (column (2): 0.41; column (4): 0.44), technical efficiency drops by 1.73-2.33%.

Firm size, as measured by logged real total assets, significantly decreases productivity in every specification. Similarly, the coefficients are interpreted as elasticities. If the variable rises by 1%, productivity significantly drops by 0.536-0.710%. In contrast to Del Bo (2013), larger firms produce significantly less efficiently than medium sized firms. Nevertheless, these studies do not consider endogeneity of firm size. When considering endogeneity, Yang & Chen (2009) also find negative effects of firm size. In the literature, however, there is no consens whether smaller or larger companies produce more efficiently or grow faster than the others. My result, therefore, is in line with the literature concluding that larger firms produce less efficiently due to their complexity in organization and agency problems (De & Nagaraj (2014), Ye *et al.* (2012), Diaz & Sanchez (2008), Yasuda (2005), Haltiwanger *et al.* (1999), Berger & Hannan (1998), Majumdar (1997), Schneider (1991)). Often negative impacts are found in developing countries (De & Nagaraj (2014), Tybout (2000)). Next, larger firms are also more likely to be public companies that produce less efficiently (Del Bo (2013)). Poorly implemented privatisations, however, established new legal monopolies instead of creating contestable markets (Buccirossi & Ciari (2018)). Hence, the results suggest that breaking up large state-owned companies (e.g. unbundling) spurred productivity in post-communist countries. In a historical sense, it supports the hypothesis that communists have not allocated resources efficiently by excessively promoting large companies that still benefit from governmental support (Buccirossi & Ciari (2018)). De Rosa *et al.* (2015), also observing negative effects of firm size on Eastern European companies' productivity, argue that the result may be a sign of incomplete restructuring (e.g.: regulations primarily targeted larger firms decreasing their efficiency). Besides, building up capacities is costly, as new plants have to be constructed (semi-fixed costs), dominating the productivity gains from economies of scale. [17] Moreover, regulation might avoid that firms exploit increasing returns to scale, i.e.: if regulated prices under incentive regulation do not completely cover investment costs, then productivity will decline when the company grows.

Following Daveri *et al.* (2016), I allow for heterogeneous effects of Lerner indexes across countries in columns (1) and (3) of *Table* 4 by interacting relevant variables with dummies for the countries. The results are ambiguous. In column (1), only the effect in the Czech Republic is significant, while in column (3), the conclusions are reversed. When not correcting the shares of material expenditures for fluctuations in output unrelated to variations in inputs when calculating the Lerner indexes from the production function, the conclusions are the same as in column (1). The result highlights the importance of the correction, as return on sales completely reflect such variations. Thus, applying return on sales could suggest different conclusions, since fluctuations in output unrelated to inputs are biasing the estimates. Significantly negative impacts in Hungary and Slovakia are plausible, as markets have been liberalised more extensively in these countries. They also implemented stricter unbundling regimes earlier. In comparison, the Czech republic liberalised less extensively and introduced unbundling later, i.e.: the market share of the largest electricity generator declined more strongly in Hungary and Slovakia than in the Czech Republic (Meletiou *et al.* (2018)). [18]
I also allow for heterogeneous impacts across three-digit NACE industries. Given the small number of gas firms, gas and electricity industries are classified as one group, as both sectors have been liberalised substantially (Meletiou *et al.* (2018), Growitsch & Stronzik (2014)), while steam and air conditioning industries are still highly concentrated, weakly regulated and characterised by local natural monopolies (European Commission (2016)). Plausibly, productivity responds more strongly to market power in the liberalised industries in which competition has increased, whereas it responds less intensively in the weakly liberalised steam and air conditioning sectors.

In *Table* 5 I allow for heterogeneous impacts of Lerner indexes across legal forms in columns (1) and (3), and regulatory quality in columns (2) and (4) to incorporate the influence of political institutions' quality (Castelnovo *et al.* (2019), Gugler *et al.* (2013)), by interacting them with relevant dummy and continuous variables. Data on legal forms are obtained from Orbis, while

[17] As shown in *Table* 2, only mild increasing returns to scale are observed.

[18] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_ind_331a&lang=en`
`https://stats.oecd.org/Index.aspx?DataSetCode=ETCR`
`https://stats.oecd.org/Index.aspx?DataSetCode=SECTREG2018`

	Lerner index (ROS)		Lerner index (Productivity)	
	Linear LI	Squared LI	Linear LI	Squared LI
	(1)	(2)	(3)	(4)
$log(TFP_{t-1})$	0.289^{***}	0.288^{***}	0.548^{***}	0.535^{***}
	(0.088)	(0.100)	(0.111)	(0.107)
Lerner index	-2.325^{***}	-0.866	-1.394^{*}	0.643
	(0.503)	(0.712)	(0.765)	(1.202)
Lerner index^2		-1.791^{**}		-2.705^{*}
		(0.831)		(1.521)
log(Real total assets)	-0.670^{***}	-0.710^{***}	-0.558^{***}	-0.536^{***}
	(0.097)	(0.109)	(0.110)	(0.107)
Time Dummies	*yes*	*yes*	*yes*	*yes*
Observations	3222	3222	3200	3200
Units	696	696	669	669
Instruments	144	158	97	109
AB test on AR(1)	-3.029^{***}	-3.024^{***}	-3.016^{***}	-3.033^{***}
AB test on AR(2)	0.919	0.796	-1.139	-0.749
AB test on AR(3)	-0.575	-0.789	-0.550	-0.787
p-value Hansen statistics	0.113	0.104	0.207	0.171

Note: The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are robust and corrected by the Windmeijer (2005) approach. Concerning the lag structure, I follow the standard approach (Roodman (2009b)). In the difference equations of columns (3) and (4), predetermined variables are instrumented with their levels lagged by one period; in columns (1) and (2) by one up to five periods. In columns (3) and (4), endogenous variables are instrumented with their levels lagged by two periods; in column (2) by two and three periods; in column (1) by two up to four periods. In the level equations, the levels of the endogenous variables are instrumented with their first differences lagged by one period and the ones of predetermined variables are instrumented with the contemporaneous first differences. The strictly exogenous variables serve as instruments for themselves. The employed instruments suffice to satisfy the Hansen tests and, thus, no further instruments are used to avoid biases stemming from weak instruments. The p-values of the Hansen statistics should not fall below 0.10 to satisfy instrument exogeneity. On the other hand, high p-values such as 0.25 also represent potential signs of trouble (Roodman (2009b), Roodman (2009a)).

*p<0.1; **p<0.05; ***p<0.01

Table 3: Regressions of $log(TFP)$ considering endogeneity

	Lerner index (ROS)		Lerner index (Productivity)	
	Country	Industry	Country	Industry
	(1)	(2)	(3)	(4)
$log(TFP_{t-1})$	$0.304***$	$0.392***$	$0.585***$	$0.562***$
	(0.088)	(0.086)	(0.095)	(0.108)
Lerner index$_{CZ}$	$-3.144***$		-0.392	
	(0.621)		(0.739)	
Lerner index$_{HU}$	-1.524		$-2.653**$	
	(1.052)		(1.100)	
Lerner index$_{SK}$	-1.023		$-2.716**$	
	(1.199)		(1.098)	
Lerner index$_{electrcity,\, gas}$		$-2.693***$		$-2.755***$
		(0.764)		(1.041)
Lerner index$_{steam,\, air}$		-0.086		-0.921
		(0.895)		(0.752)
log(Real total assets)	$-0.664***$	$-0.614***$	$-0.535***$	$-0.421***$
	(0.090)	(0.081)	(0.104)	(0.091)
Time Dummies	*yes*	*yes*	*yes*	*yes*
Observations	3222	3222	3200	3200
Units	696	696	669	669
Instruments	143	111	119	137
AB test on AR(1)	$-3.015***$	$-4.035***$	$-3.450***$	$-3.401***$
AB test on AR(2)	1.056	1.344	-0.773	-1.024
AB test on AR(3)	-0.645	-0.890	-0.179	-0.204
p-value Hansen statistics	0.115	0.126	0.197	0.170

Note: The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are robust and corrected by the Windmeijer (2005) approach. Concerning the lag structure, I follow the standard approach (Roodman (2009b)). In the difference equations of columns (2)-(4), predetermined variables are instrumented with their levels lagged by one period; in column (1) by one up to three periods. In columns (1)-(3), endogenous variables are instrumented with their levels lagged by two periods; in column (4) they are instrumented with the levels lagged by two up to six periods. In the level equations, the levels of the endogenous variables are instrumented with their first differences lagged by one period and the ones of predetermined variables are instrumented with the contemporaneous first differences. The strictly exogenous variables serve as instruments for themselves. The employed instruments suffice to satisfy the Hansen tests and, thus, no further instruments are used to avoid biases stemming from weak instruments. The p-values of the Hansen statistics should not fall below 0.10 to satisfy instrument exogeneity. On the other hand, high p-values such as 0.25 also represent potential signs of trouble (Roodman (2009b), Roodman (2009a)).

*p<0.1; **p<0.05; ***p<0.01

Table 4: Regressions of $log(TFP)$ considering endogeneity and heterogeneity across countries and industries

regulatory quality indexes are sourced from the Worldbank. [19] The better are the peoples' perceptions of the governments' abilities to formulate and implement sound regulation promoting private sector development, the higher is the index, lying between -2.5 and 2.5.
Plausibly, productivity of private limited companies responds more sensitively to competitive pressure than public limited companies, as disclosure requirements are stricter for public limited companies already providing shareholders a better context to assess corporate performance to push managers to reduce managerial slack. Given the weaker regulations for private limited companies, fiercer competition allows stockholders to more precisely evaluate company performance than under weaker competition.
Last, the impact of competitive pressures plausibly declines when regulatory quality increases. Governments impose and execute policies to support shareholders to assess company performance forcing managers to keep costs under control also under weaker competition. Thus, competitive pressure as a complement tool to provide stockholders a better context to evaluate firm performance loses some effectiveness. In the analysed countries, regulatory quality, ranging from 0.603 to 1.312, worsened over time, boosting competition's relevance. Nevertheless, interaction terms are only significant in column (4). In column (2) the p-value of the interaction is 0.119 closely to 0.10. Effects range from -2.40 to -1.66 (mean: -1.96) in column (2), and from -1.18 to -0.28 (mean: -0.64) in column (4).

3.3 Discussion

To foster competition in energy sectors, European member states have implemented several policies (e.g. vertical disintegration, removal of market barriers, privatisations) aiming to spur productive and allocative efficiency. Despite these policies, many segments are still highly concentrated. Therefore, this study sheds light on the effects of competitive pressure on energy firms' productivity. Being the first study establishing the linkage between competition and technical efficiency of energy firms and measuring Lerner indexes with the algorithm by De Loecker & Warzynski (2012), I find that market pressure significantly boosts productivity supporting many studies observing a negative effect of market power on technical efficiency.

As pointed out in previous sections, the results of the first stage may suffer from input and output price biases. While input price biases and the critique by Gandhi *et al.* (2020) can be addressed by involving demand shifters, production function estimates are still contaminated by output price biases. On the other hand, the goal of this study is not to consistently estimate production functions, but to obtain consistent effects of derived Lerner indexes on productivity. Therefore, implied measurement errors are taken account of by applying system GMM in the second stage. Coefficients of interest are consistent, while the coefficient of the lagged dependent variable is biased.

Results of both stages are overall not sensitive to changes in the specification. First, introducing approximated market shares as demand shifters in the first stage, barely changes them.

[19] `https://info.worldbank.org/governance/wgi/`

	Lerner index (ROS)		Lerner index (Productivity)	
	Legal form	Regulatory quality	Legal form	Regulatory quality
	(1)	(2)	(3)	(4)
$log(TFP_{t-1})$	0.369^{***}	0.467^{***}	0.442^{***}	0.625^{***}
	(0.104)	(0.112)	(0.085)	(0.083)
Lerner index$_{public\,limited}$	-0.659		-0.746	
	(0.625)		(0.671)	
Lerner index$_{private\,limited}$	-2.334^{***}		-2.477^{***}	
	(0.622)		(0.766)	
Lerner index		-3.034^{***}		-1.939^{**}
		(0.860)		(0.827)
Lerner index· regulatory quality		1.044		1.262^{*}
		(0.670)		(0.698)
log(Real total assets)	-0.662^{***}	-0.563^{***}	-0.622^{***}	-0.451^{***}
	(0.096)	(0.110)	(0.093)	(0.086)
Time Dummies	*yes*	*yes*	*yes*	*yes*
Observations	3222	3200	3222	3200
Units	696	669	696	669
Instruments	111	130	153	137
AB test on AR(1)	-3.375^{***}	-2.932^{***}	-3.889^{***}	-3.922^{***}
AB test on AR(2)	0.954	-1.159	0.845	-0.586
AB test on AR(3)	-1.007	-0.158	-0.748	-0.472
p-value Hansen statistics	0.192	0.113	0.109	0.105
Note:	The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are robust and corrected by the Windmeijer (2005) approach. Concerning the lag structure, I follow the standard approach (Roodman (2009b)). In the difference equations of columns (1), (2) and (4), predetermined variables are instrumented with their levels lagged by one period; in column (3) by one up to three periods. In columns (1) and (3), endogenous variables are instrumented with their levels lagged by two periods; in column (4) by two up to six periods; in column (2) by two up to eight periods. In the level equations, the levels of the endogenous variables are instrumented with their first differences lagged by one period and the ones of predetermined variables are instrumented with the contemporaneous first differences. The strictly exogenous variables serve as instruments for themselves. The employed instruments suffice to satisfy the Hansen tests and, thus, no further instruments are used to avoid biases stemming from weak instruments. The p-values of the Hansen statistics should not fall below 0.10 to satisfy instrument exogeneity. On the other hand, high p-values such as 0.25 also represent potential signs of trouble (Roodman (2009b), Roodman (2009a)). *p<0.1; **p<0.05; ***p<0.01			

Table 5: Regressions of $log(TFP)$ considering endogeneity and heterogeneity across legal forms and company category

Second, defining material and labour as the inputs free of adjustment costs when calculating Lerner indexes from the production function, results overall stay robust too. [20] Third, the analogous holds when estimating production functions for each three-digit NACE industry pooling observations across countries.

4 Conclusion

In this work, I investigate the effects of market power on productivity of Czech, Hungarian and Slovak energy firms, as a long-held proposition states that competition spurs firm-level productivity. Besides, analysing energy sectors is of particular interest, because they are still highly concentrated, although they have been liberalised (e.g. elimination of market barriers, vertical disintegration, privatisation) fostering competition. Furthermore, examined countries are post-communist experiencing major institutional changes and liberalisations, although the government's influence in these countries is still pervasive. Especially post-communist countries are characterised by strong entry barriers aggravating the transition to well-functioning market economies. Furthermore, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies strengthening market barriers (Buccirossi & Ciari (2018)). To establish a link between market pressure and technical efficiency, I employ a two-staged framework. In the first stage, I estimate a three-input revenue-based translog production functions with the algorithm by Ackerberg *et al.* (2015), using a dataset on energy firms from 2009 to 2017, to obtain productivity. In the second stage, productivity is regressed on firm-level Lerner indexes and control variables applying system GMM estimation to consider the endogeneity of competition. Firm-level Lerner indexes are calculated in two ways. First, I calculate them return on sales-style. Second, the framework by De Loecker & Warzynski (2012) is used to obtain them directly from the production function estimates.

Supporting the literature, especially the simple oligopoly models, Leibenstein (1966) and the 'Quiet Life' hypothesis, the results show that market power significantly drops productivity. In other words, competition forces firms to innovate and to eliminate managerial slack to survive market pressures. Moreover, larger firms produce significantly less efficiently. Policy makers, intending to restructure energy markets, should, therefore, foster market liberalisation and eliminate further entry barriers. For instance, politicians may facilitate price comparisons and encourage consumers to switch suppliers more frequently. Nevertheless, particular liberalisation policies such as vertical disintegration come with a cost, as economies of scope disappear, implying that efficiency losses may exceed productivity gains of fiercer competition (Gugler *et al.* (2017)).

[20]In the regressions introducing squared Lerner indexes and investigating country-specific effects of Lerner indexes, coefficients of interest turn slightly insignificant.

Appendices

E The method by Ackerberg/Caves/Frazer

When estimating production functions, much consideration needs to be given to identification problems. First, simultaneity biases arise because of the endogeneity of inputs, i.e.: firms with positive productivity shocks demand larger input amounts. Hence, inputs correlate with unobserved productivity. Second, attrition in the data causes identification problems, because firms with high productivity levels have a higher probability to survive, while firms with low levels of productivity are more likely to exit the market (Levinsohn & Petrin (2003), Olley & Pakes (1996), Marschak & Andrews (1944)).

Unlike Olley & Pakes (1996) and Levinsohn & Petrin (2003), Ackerberg *et al.* (2015) allow for a dynamic specification in the choice of labour by claiming that labour also depends on unobserved productivity. In other words, it assumes that labour is chosen prior to other flexible inputs, or is dynamic and subject to adjustment costs. Hence, the coefficients of free variables (e.g. labour) cannot be correctly identified in the first stages of Olley & Pakes (1996) and Levinsohn & Petrin (2003). Instead, the coefficients are estimated in the second stage. To get the intuition, imagine a subperiod between periods $t-1$ and t. First, the firm chooses the optimal amount of material. Second, the productivity shock occurs in the subperiod. Third, the amount of labour is purchased. Now, labour is an element of the demand function for material in period t, which is still invertible as long as m is strictly increasing in productivity.

In the first stage, I run

$$y_{i,t} = \phi_{i,t}(l_{i,t}, k_{i,t}, m_{i,t}) + \psi_{i,t} \tag{E.1}$$

to obtain estimates for the expected output $\hat{\phi}_{i,t}$ and the productivity shock $\hat{\psi}_{i,t}$. The expected output is

$$\begin{aligned}\phi_{i,t} = &\beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + \\ &\beta_{kk} \cdot k_{i,t}^2 + \beta_{ll} \cdot l_{i,t}^2 + \beta_{mm} \cdot m_{i,t}^2 + \\ &\beta_{kl} \cdot k_{i,t} \cdot l_{i,t} + \beta_{km} \cdot k_{i,t} \cdot m_{i,t} + \\ &\beta_{lm} \cdot l_{i,t} \cdot m_{i,t} + h_t^{-1}(m_{i,t}, k_{i,t})\end{aligned} \tag{E.2}$$

with $h^{-1}(.)$ being the inverted demand for material. Assuming that the demand for material is strictly monotonically increasing in productivity allows to invert the demand function to obtain productivity as a function of the proxy and state variable. Unobserved productivity ω is substituted with the inverted function in equation (E.2).

In the second stage, estimates for all production function coefficients $\beta = (\beta_k, \beta_l, \beta_m, \beta_{kk}, \beta_{ll}, \beta_{mm}, \beta_{kl}, \beta_{km},$

are calculated by relying on the law of motion of productivity

$$\omega_{i,t} = g_t(\omega_{i,t-1}, a_{i,t-1}) + \xi_{i,t} \tag{E.3}$$

using equation (E.4). a is the demand shifter that affects the demand for material m, but does not directly enter the production function as an input.

$$\begin{aligned}\omega_{i,t}(\beta) = &\phi_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} - \\ &\beta_{kk} \cdot k_{i,t}^2 - \beta_{ll} \cdot l_{i,t}^2 - \beta_{mm} \cdot m_{i,t}^2 - \\ &\beta_{kl} \cdot k_{i,t} \cdot l_{i,t} - \beta_{km} \cdot k_{i,t} \cdot m_{i,t} - \beta_{lm} \cdot l_{i,t} \cdot m_{i,t}\end{aligned} \tag{E.4}$$

Non-parametrically regressing $\omega(\beta)$ on its lag recovers the innovations to productivity ξ, required to form moment conditions, used to estimate the coefficients β with GMM. To obtain the standard errors of β, I rely on cluster bootstrapping.

$$\begin{aligned}&E[\xi_{i,t} \cdot k_{i,t}] = 0\\ &E[\xi_{i,t} \cdot l_{i,t-1}] = 0\\ &E[\xi_{i,t} \cdot m_{i,t-1}] = 0\\ &E[\xi_{i,t} \cdot k_{i,t}^2] = 0\\ &E[\xi_{i,t} \cdot l_{i,t-1}^2] = 0\\ &E[\xi_{i,t} \cdot m_{i,t-1}^2] = 0\\ &E[\xi_{i,t} \cdot k_{i,t} \cdot l_{i,t-1}] = 0\\ &E[\xi_{i,t} \cdot k_{i,t} \cdot m_{i,t-1}] = 0\\ &E[\xi_{i,t} \cdot l_{i,t-1} \cdot m_{i,t-1}] = 0\end{aligned} \tag{E.5}$$

F The method by De Loecker and Warzynski

To obtain markups, suppose the following production function. Y denotes the level of output, K capital, L employment, M material and ζ the sum of unobserved productivity and the productivity shock. Again, indices i and t represent firms and years.

$$Y_{i,t} = Y_{i,t}(K_{i,t}, L_{i,t}, M_{i,t}, \zeta_{i,t}) \tag{F.1}$$

Assuming that active firms minimize costs allows to formulate the associated Lagrangian function with r, w, p_M and λ being the interest rate, wage, material price and Lagrange multiplier.

$$\mathcal{L} = r_{i,t} \cdot K_{i,t} + w_{i,t} \cdot L_{i,t} + p_{M,i,t} \cdot M_{i,t} + \lambda_{i,t} \cdot (Y_{i,t} - Y_{i,t}(\cdot)) \tag{F.2}$$

The first-order condition for any input free of adjustment costs (in this case material) is described in equation (F.3). Given the cost minimization problem, the Lagrangian multiplier equals the marginal costs of production c.

$$\frac{\partial \mathcal{L}}{\partial M_{i,t}} = p_{M,i,t} - \lambda_{i,t} \cdot \frac{\partial Y_{i,t}(\cdot)}{\partial M_{i,t}} = 0 \tag{F.3}$$

Rearranging equation (F.3) and multiplying both sides with $\frac{M_{i,t}}{Y_{i,t}}$ generates equation (F.4) implying that cost minimization requires the firm to equalize the output elasticity of material with the right-hand side of the equation.

$$\underbrace{\frac{\partial Y_{i,t}}{\partial M_{i,t}} \cdot \frac{M_{i,t}}{Y_{i,t}}}_{\frac{\partial y_{i,t}}{\partial m_{i,t}}} = \frac{1}{\lambda_{i,t}} \cdot \frac{p_{M,i,t} \cdot M_{i,t}}{Y_{i,t}} \tag{F.4}$$

Next, the expression for the price-cost margin $\mu_{i,t} = \frac{P_{Y,i,t}}{\lambda i,\, t}$, which is robust to various static price setting models and does not require any assumptions on the particular form of price competition between firms, is plugged in into equation (F.4). Nevertheless, this assumes that companies set prices every period ruling out dynamics in pricing. In comparison, a full profit maximisation problem may also be considered. Nonetheless, cost minimization problems are part of profit maximisation problems and, therefore, suffice to derive price-cost margins. Furthermore, profit maximisation requires to introduce additional assumptions (e.g. type of competition) substantially raising complexity (Koppenberg & Hirsch (2021), Basu (2019), De Loecker & Warzynski (2012)). Now, the output elasticity of material equals the price-cost margin times the share of nominal material expenditures in nominal revenue θ computable from the data. As in De Loecker & Warzynski (2012), I correct θ for fluctuations stemming from variations in output unrelated to variables impacting input demand by multiplying it with the exponentiated productivity shock from the first stage $e^{\psi_{i,t}}$.

$$\frac{\partial y_{i,t}}{\partial m_{i,t}} = \mu_{i,t} \cdot \underbrace{\frac{p_{M,i,t} \cdot M_{i,t}}{p_{Y,i,t} \cdot Y_{i,t}}}_{\theta_{i,t}} \tag{F.5}$$

Last, solving for the price-cost margin and plugging the resulting identity into the equation of the Lerner index LI gives

$$\begin{aligned} LI_{i,t} &= \frac{p_{Y,i,t} - c_{i,t}}{p_{Y,i,t}} \\ &= 1 - \frac{c_{i,t}}{p_{Y,i,t}} \\ &= 1 - \frac{1}{\mu_{i,t}} \end{aligned} \tag{F.6}$$

May it be a little bit more of Market Concentration? On Productivity Growth and Competition

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Abstract: In its heart, competition represents an important driver of productivity growth that has slowed in European countries since the financial crisis. This study examines the non-linear relationship between productivity growth and market concentration, using data on Central European manufacturing firms, from 2009 to 2017. The results show concave relationships between both variables and that firms in competitive industries respond more sensitively to market concentration. This study contributes to the literature by not only applying the standard firm-level measure of Lerner indexes, but calculates them from production functions, and checking robustness with alternative country-industry-level concentration measures.

JEL: D22, D24, D47, L11, L51

Keywords: Firm Growth, Productivity, Market Structure, Concentration, Manufacturing Regulation

1 Introduction

One prominent research question in productivity analysis is the effect of competition on firm-level innovation and productivity growth. According to Schumpeter (1934), monopolists invest more in R&D due to less market uncertainty providing greater funds and more stable sources of income. Similarly, the leading models on product differentiation by Dixit & Stiglitz (1977) and Salop (1979), and many textbook models on endogeneous growth predict that more intense competition decreases postentry rents, discouraging innovation and productivity growth. Conversely, Arrow (1962) argues that innovative firms benefit more from innovation when competition is fierce. In comparison, Aghion *et al.* (2005) observe concave relationships between competition and innovation motivating them to build a theoretical model combining both views. Additionally, they claim that industry-specific gaps to the productivity frontier increase with intensifying competition and that firms in competitive industries respond more strongly to competition. To provide empirical evidence on this model's propositions, I examine the impacts of Lerner indexes on productivity growth employing micro-data on Austrian, Czech, Hungarian Slovak, and Slovenian manufacturing firms from 2009 to 2017. Analysing Central European manufacturing sector is of particular interest. Manufacturing is considered the main source of technological progress, although service sectors take over higher shares of national output at the cost of manufacturing given the development of demand structures and outsourcing (Baumol (1967)). Central Europe is compelling for two reasons. First, relevant countries constitute small open economies. Second, as outlined in *Section 2*, they are either post-communist or belong to the Central European core, an industrial region that has rapidly grown in the previous decades.

Owing to the improving availability of firm-level data, many studies empirically examining the Schumpeterian hypothesis conclude that competition spurs innovation and productivity growth. Syverson (2004) investigates the link between productivity and competition finding that competition raises productivity by wiping out inefficient firms. Similarly, Disney *et al.* (2003) conclude that competition spurs technical efficiency. Besides, Nickell (1996) and Nickell *et al.* (1997) observe that competition improves corporate productivity growth. Okada (2005) also finds positive impacts of competition on firm-level productivity. In comparison, Blundell *et al.* (1999) regress headcount innovation measures of major technological breakthroughs and conclude that market shares spur innovation, while market concentration decreases it. Tang (2006), following Blundell *et al.* (1999), shows that the relationship between competition and innovation depends on the measure of competition. The empirical and theoretical findings by Aghion *et al.* (2005) are supported by Hashmi (2013) (for the UK, but not for the US), Inui *et al.* (2012) and Tingvall & Poldahl (2006). Contrarily, Aghion *et al.* (2008) observe a convex function between productivity growth and firm-level Lerner indexes in Africa. The same holds for Atayde *et al.* (2021) finding a convex, though insignificant, relationship between R&D variables, productivity and competition measures.

This work contributes to the literature in several aspects. First, my dataset covers smaller firms next to large or listed firms (e.g. Hashmi (2013)) enabling a more comprehensive analysis. Second, to the best of my knowledge, this is the first study measuring Lerner indexes employing the framework proposed by De Loecker & Warzynski (2012) next to the conventional return on sales-definition when examining the theoretical propositions. Third, I check robustness with country-industry-specific measures of market concentration.

Overall, I find a concave relationship between productivity growth and market concentration supporting several studies discussed. However, the effect of market concentration on country-industry-specific gaps to the productivity frontier depends on the measurement of Lerner indexes. Last, firms operating in competitive industries respond more strongly to market concentration.

The paper proceeds as follows. *Section 2* provides an overview on the Central European manufacturing sector. *Section 3* introduces the empirical framework and data, while *Section 4* provides the results of the production function estimations and the regressions of firm and industry performance. Last, *Section 5* sums up and draws conclusions.

2 Background and hypothesis

2.1 Central European manufacturing sectors

Analysing Central European countries is interesting for many reasons. First, many Central European countries (in the sample: 4 out of 5) are post-communist. After the collapse of the Soviet Unvion they have transitioned from centrally planned to market economies experiencing major institutional changes and liberalizations, although the government's influence in these countries is still pervasive. Especially post-communist countries are characterized by strong entry barriers aggravating the transition to well-functioning market economies. Moreover, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies strengthening market barriers (Buccirossi & Ciari (2018)).

Second, as outlined by a study of the IMF (2013), Europe's manufacturing activity increasingly concentrates in a Central European core consisting of Austria, the Czech Republic, Germany, Hungary, Slovakia and Poland. Especially, the role of Austria is interesting given its intermediate position, since it is neither an offshoring destination nor the technology leader. In the Central European core, structural shifts towards service industries were less pronounced than in other countries; in Hungary and Slovakia manufacturing's share in GDP even increased. Furthermore, since the 2000s the relevant countries' manufacturing export intensities have risen more sharply than in other EU countries raising their export market shares at the cost of other EU states (e.g. France, UK). As the most important manufacturing sectors, the main drivers of this development cover machinery, metal, electrical products, vehicles and chemical industries (Stehrer & Stöllinger (2014), IMF (2013)). [1]
This development was even fuelled by the Eastern European expansion of the EU. As shown in *Figure* 1, manufacturing sectors' real labour productivity growth rates, however, have declined

[1] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en

in many European countries temporarily or permanently, especially in post-communist member states, since the financial crisis. [2] Particularly, in Central European countries, labour productivity growth rates, however, evolved differently across countries and industries. In the food, beverages and tobacco; textile, wearing apparel and leather; wood; paper; printing and media; chemical; pharmaceutical; rubber and plastics; non-metallic minerals; basic metal; fabricated metal; computer, electronic and optical product; electrical equipment; machinery; motor vehicle; other transport equipment; furniture; repair and installation industries growth rates of real gross value added by working hour dropped severely during the financial crises, but recovered again. Depending on the country, they recovered faster or more slowly. In some of them (e.g. wood; paper; printing and media; pharmaceutical; rubber and plastics; fabricated metal; computer, electronic and optical product; repair and installation), the decline was permanent, as growth rates stabilized at lower levels, particularly in the post-communist countries. [3]

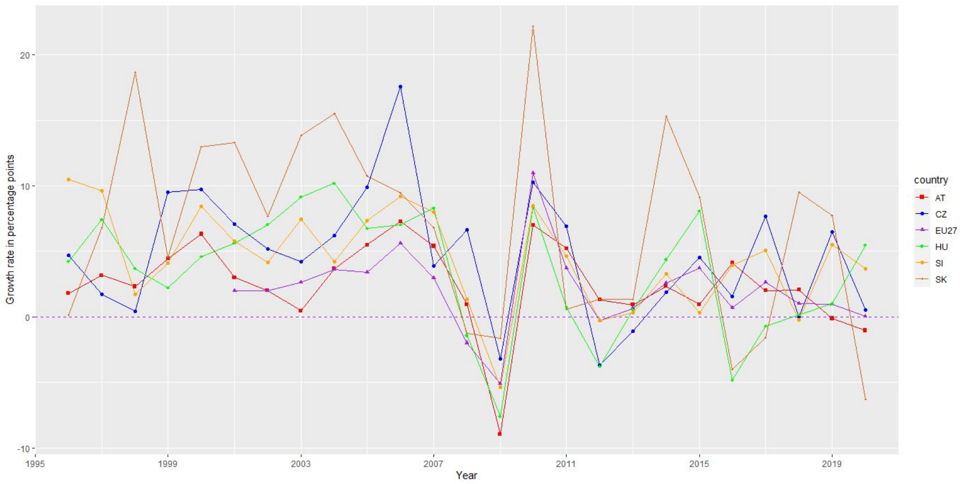

Figure 1: Growth rates of real gross value added per worker in manufacturing (C) by country and year

Data Source: Eurostat [4]

2.2 Examined propositions

Although the models by Dixit & Stiglitz (1977) and Salop (1979) conclude that fiercer competition deteriorates postentry rents and, finally, discourages innovation and reduces the equilibrium number of entrants, Aghion *et al.* (2005) observe concave relationships between innovation and competition. Therefore, they set up a theoretical model that does not only account for negative effects of competition on productivity growth, but also explains the increasing part of the inverted-u shaped relationship.

According to Aghion *et al.* (2005), the economy consists of two kinds of sectors: *leveled* or *neck-and-neck* sectors where firms are technological par with one another, and *unleveled* sectors

[2] Growth rates are calculated as follows. Chained gross value added is divided by the total number of working hours by employed and self-employed. Then, the growth rate is calculated.

[3] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en`
`https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64_e&lang=en`

[4] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64&lang=en`,
`https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nama_10_a64_e&lang=en`

characterized by one leading firm (*leader*) lying one step ahead its competitors (*laggards* or *followers*). In the first type, firms innovate to differentiate themselves from competitors temporarily escaping from competition and to benefit from monopoly rents, while in the second type, laggards innovate to catchup with the leader. In case of weak product market competition, neck-and-neck firms only face weak incentives to innovate. Consequently, the overall innovation rate will be higher in unleveled industries. Thus, the industry will quickly leave the unleveled state, which it does when laggards start innovating, and slowly leaves the leveled state, which will not happen until neck-and-neck firms innovate. This implies that industries spend most of the time in the leveled state dominated by escape-competition. In other words, if competition intensity increases starting from a low level, innovation rates and productivity growth are high. Conversely, when competition intensity is high to begin with, there is hardly incentive for laggards in an unleveled state to innovate (*Schumpeterian effect*), suggesting that the industry will be slow to leave the unleveled state. In the leveled industry, however, innovation rents spur firms to innovate to escape competition (*escape-competition effect*) such that the industry quickly moves to the unleveled state where laggards innovate to catchup, while leaders do not. Summing up, in case of an intense initial competition, increasing competition drops innovation and productivity growth rates.

The second proposition of the model by Aghion *et al.* (2005) suggests that industry-specific expected technology gaps increase with competition. Although the static intuition suggests that intensifying competition decreases the gap by wiping out inefficient firms, the model by Aghion *et al.* (2005) implies that the fiercer competition is, firms conduct more research in neck-and-neck industries, but less in unleveled sectors. Consequently, the same holds for the entire economy due to the law of large numbers.

Last, the third proposition of Aghion *et al.* (2005) claims that there is a positive interaction between the country-industry-level average distance to the frontier and escape-competition effect. In other words, the escape-competition effect is stronger in sectors where companies are closer to the frontier, i.e.: productivity growth maximizing levels of competition are smaller in neck-and-neck industries.

This study examines the propositions of the discussed model using firm data on the Central European manufacturing sectors being of particular interest given their economic development and historical conditions.

3 Empirical strategy and data

This section describes the empirical strategy consisting of two stages. In the first stage, I estimate production functions allowing to obtain firm-level productivity, whose growth rate is regressed in the second stage. In the second stage, the analysis is threefold. First, productivity growth is explained by competition at the firm-level to investigate the first proposition. Second, country-industry-specific average productivity gaps are related to competition varying at the same level.

Third, the heterogeneous effects of market power are examined across competitive and not-competitive sectors.

3.1 First stage: estimation of the production function

To establish links between market concentration and productivity growth, a two-stage procedure is employed. Following the literature (e.g. Gemmell *et al.* (2018), Richter & Schiersch (2017), Collard-Wexler & De Loecker (2015), Lu & Yu (2015), Du *et al.* (2014), Del Bo (2013), Doraszelski & Jaumandreu (2013), Crinò & Epifani (2012), De Loecker & Warzynski (2012), Arnold *et al.* (2011), De Loecker (2007a), Javorcik (2004)), I estimate three-input revenue-based Cobb-Douglas production functions, as described in equation (1), with the method by Ackerberg *et al.* (2015) explained in appendix G. y denotes logged output (dependent variable), k logged capital (state variable), l logged labour (free variable), and m logged material (proxy variable). ζ is the sum of unobserved productivity ω and measurement errors of productivity shocks ψ. Indices i and t represent firms and years. A Cobb-Douglas specification is chosen due to its popularity in the literature, although translog specifications are more flexible, though data demanding (Syverson (2011)).

$$y_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + \underbrace{\omega_{i,t} + \psi_{i,t}}_{\zeta_{i,t}} \tag{1}$$

As product-level output and input quantities are usually not available, while monetary outputs and inputs are mostly provided as firm-level aggregates, I follow the literature and estimate gross output production functions using producers' real total monetary outputs and inputs.
To consider heterogenous input elasticities β across countries, I follow the majority of studies (e.g. Fons-Rosen *et al.* (2021), Levine & Warusawitharana (2021), Gemmell *et al.* (2018), Olper *et al.* (2016)) and estimate equation (1) for each two-digit NACE industry-country combination. As productivity is the residual, it measures the shifts in output while keeping inputs constant. Owing to the logged dependent variable, productivity is also logged, as shown in equation (2) (Javorcik (2004), Olley & Pakes (1996)).

$$log(TFP_{i,t}) = y_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \tag{2}$$

3.1.1 Data

In this work, I use the same data as in Steinbrunner (2021). Firm-level data are sourced from the Orbis database published by Bureau van Dijk. Orbis contains accounting data, legal form, industry activity codes, and incorporation date for a large set of public and private companies worldwide. I include active and inactive; medium sized, large and very large [5] European manufacturing companies (NACE C1000 - C3320), incorporated in five countries: Austria, the Czech Republic, Hungary, Slovakia and Slovenia. The final sample is a nine-year unbalanced panel dataset, from 2009 to 2017, containing 18,060 firms with 123,101 observations of 24 two-digit NACE industries (94 three-digit and 265 four-digit NACE industries). [6]

Output is defined as real operating revenues, being the sum of net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk (2007)) deflated by annual gross value added deflators from the OECD database [7], varying across countries, two-digit NACE industries and years. Next, capital is approximated with tangible fixed assets (e.g.: machinery) deflated by uniform investment good price indexes from the same database [8], varying across countries and years. Third, labour is a physical measure of the number of employees included in the company's payroll. Fourth, material is measured by real material expenditures, being the sum of expenditures on raw materials and intermediate goods deflated by uniform intermediate good price indexes from the same database [8], varying across countries and years (Castelnovo *et al.* (2019), Richter & Schiersch (2017), Newman *et al.* (2015), Du *et al.* (2014), Nishitani *et al.* (2014), Baghdasaryan & la Cour (2013), Javorcik & Li (2013), Crinò & Epifani (2012), Higón & Antolín (2012), Javorcik (2004)).

However, one set of econometric issues results from employing deflated monetary values of inputs instead of quantities. Potential differences in input prices across firms, implied by differences in the access to input markets or monopsony positions, might cause the 'input price bias'. When ignoring this issue, the framework implicitly assumes that all firms face identical input prices. Hence, derived estimates would suffer from input price biases, in case of input price differences. Resulting coefficients are biased downwards, while constructed productivity, finally, is biased upwards. In this work, I only rely on two deflated monetary inputs, capital and material, potentially causing biased coefficients, while labour is measured physically (De Loecker & Goldberg (2014)). Furthermore, Gandhi *et al.* (2020) show that material demand may not completely reflect productivity complicating the identification of revenue-based production functions. To tackle these problems, I follow the literature (e.g. Doraszelski & Jaumandreu (2021), Gandhi *et al.* (2020), Garcia-Marin & Voigtländer (2019), Doraszelski & Jaumandreu (2018), Lu & Yu (2015), Doraszelski & Jaumandreu (2013), De Loecker & Warzynski (2012)) and introduce a demand shifter a. Usually, these papers involve firm-level lagged real input prices, exports etc. Like Doraszelski & Jaumandreu (2021), Gandhi *et al.* (2020), Doraszelski & Jaumandreu (2018), Doraszelski & Jaumandreu (2013) I include the lagged input price of labour, the lagged average real wage per worker. [9] It does not enter the production function as an input,

[5] Orbis considers firms to be 'medium sized', when operating revenues $\geq$ 1 mill. EUR or total assets $\geq$ 2 mill. EUR or employees $\geq$ 15. Orbis defines firms to be 'large', when operating revenues $\geq$ 10 mill. EUR or total assets $\geq$ 20 mill. EUR or employees $\geq$ 150. Firms are 'very large', when operating revenues $\geq$ 100 mill. EUR or total assets $\geq$ 200 mill. EUR or employees $\geq$ 1,000 or the company is listed (Bureau van Dijk (2007)).

[6] Observations with implausible output and input values (e.g. negative values, values almost zero), missing values, unknown activity status or industry affiliation are dropped.

[7] https://stats.oecd.org/Index.aspx?DataSetCode=SNA_TABLE6A

[8] https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI

[9] Doraszelski & Jaumandreu (2018) also show that the real price of labour is more relevant than the real price of material. Besides, as fossil fuels and raw materials are traded at the stock exchange, only little variation across

but affects the demand for material and, therefore, is part of the polynomial used to proxy for unobserved productivity. In other words, omitted firm-level input prices are assumed to be a reduced-form function of the demand shifter which is interacted with deflated inputs (Gandhi *et al.* (2020), Doraszelski & Jaumandreu (2018), Lu & Yu (2015), De Loecker & Warzynski (2012)). Given the lag, every firm's first observation will be dropped. Data on firm-level wage costs are sourced from Orbis as well, which are deflated by national consumer price indices, downloaded from Eurostat [10], and divided by firm-level employment. Alternatively, some studies (e.g. Raval (2020)) suggest to calculate the production function's coefficients non-parametrically as the shares of input costs in output assuming a Cobb-Douglas production function with constant returns to scale. Relevant methods might generally be applicable to manufacturing sectors. For some particular industries, however, the assumption is too restrictive.

Next, a further set of econometric issues is implied applying deflated monetary values of output instead of quantities ('output price bias'). Although firm-level or even product-level price indices would be necessary, they are usually not available. Price indices, however, are only available at some industry-level. Applying industry-level price indices to firm-level operating revenues causes biased coefficients of the production function, if firm- or product-level prices deviate from the development of the industry-level price index, which are captured by the error term. The direction of each coefficient's bias is not straightforward and can go in either direction (De Loecker (2007b), De Loecker & Goldberg (2014), Klette & Griliches (1996)). To solve this problem, in the spirit of Klette & Griliches (1996), De Loecker (2007b) proposes a framework, based on including industry-specific aggregate demand shifters, which, however, fails to correctly identify the coefficients, because multiplying all asymmetrically biased input coefficients with a constant cannot yield unbiased input coefficients (Ornaghi (2006)). Consequently, the first stage estimates will suffer from output price biases.

3.2 Second stage: determinants of firm behaviour

In this subsection, I describe the second stage of the empirical analysis employed to empirically examine the propositions of the theoretical mode relating productivity growth to competition.

3.2.1 First proposition: concave relationship between productivity growth and competition

To examine the first proposition, I employ fixed effects regressions of firm-level productivity growth on Lerner indexes, their squares, some covariates, nested country-year and industry-year dummies (Inui *et al.* (2012), Aghion *et al.* (2008)), as described in equation (3). The indices i, t, s and c denote firms, years, three-digit NACE industries and countries, with S and C being

firms is expected. Hence, average real wages are the preferred choice.

[10] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de`

the total numbers of three-digit NACE industries and countries.

$$\begin{aligned}\Delta log(TFP_{i,t}) =& \delta_1 \cdot LI_{i,t} + \delta_2 \cdot LI_{i,t}^2 + \beta \cdot X_{i,t-1} \\ &+ \alpha_i + \sum_{c=1}^{C} \sum_{t=2011}^{2017} \gamma_{c,t} \cdot D_c \cdot D_t + \sum_{s=1}^{S} \sum_{t=2011}^{2017} \sigma_{s,t} \cdot D_s \cdot D_t + \epsilon_{i,t}\end{aligned} \tag{3}$$

The dependent variable is the firm-level growth rate of productivity, being the first difference in logged productivity (Inui *et al.* (2012)). Firm-level Lerner indexes LI and their squares are the variables of interest for which I expect to show concave relationships with the dependent variable. Unlike Atayde *et al.* (2021), Inui *et al.* (2012), Aghion *et al.* (2008) and Aghion *et al.* (2005), I do not use inverses (e.g. 1 - LI), but estimate the effect of market concentration. This approach does not only show the same functional form, but allows to verify robustness by applying other not invertible concentration measures (e.g. Theil indexes). I employ two measures of Lerner indexes. The first one is the return on sales, being the share of variable profits in revenues (Atayde *et al.* (2021), Inui *et al.* (2012), Aghion *et al.* (2008)). As the dataset does not contain data on profits, I define profits as the difference between real operating revenues and the sum of real material costs and wage expenditures following Aghion *et al.* (2008) which simplies to one minus the shares of real wages and real material costs in real operating revenues. Although this measure does not include capital costs (e.g. interest costs), as they are mostly missing, Aghion *et al.* (2008) show that deducting capital costs barely changes the results. As the second measure, I employ Lerner indexes derived by the algorithm by De Loecker & Warzynski (2012) as explained in appendix H. Firm-level Lerner indexes are directly calculated from the production function. Given the firm's optimisation problem, firm-level price-cost ratios are derived directly from the production function by dividing the coefficient of the input free of adjustment costs by its share of expenditures in operating revenues. The expenditure share is adjusted by variations in output unrelated to fluctuations in input demand. Resulting price-cost ratios are then transformed to compute Lerner indexes. Following the majority of studies (e.g. Lu & Yu (2015), De Loecker & Warzynski (2012)), I use material as the input free of adjustment costs. In contrast to labour, material is more flexible and less prone to adjustment costs, i.e.: hiring and firing is costly, while adjusting material stocks is simpler given the advanced inventory management (De Loecker & Warzynski (2012)). Moreover, the algorithm by Ackerberg *et al.* (2015) supports picking material. It assumes that labour is chosen prior to other flexible inputs, or is dynamic and subject to adjustment costs. On the other hand, the choice of the variable free of adjustments is crucial, as pointed out by some studies (e.g. Doraszelski & Jaumandreu (2021), Raval (2020)), since results depend on the variable chosen. [11]

For both specifications, only observations with $LI \in [0,1]$ are included, as Lerner indexes lying outside the interval imply either that prices do not cover marginal costs, some products of multi-

[11] As pointed out in *Section* 3.1.1, Raval (2020) suggests to calculate the production function's coefficients non-parametrically as the shares of input costs in revenues assuming a Cobb-Douglas production function with constant returns to scale. Nevertheless, the assumption of constant returns to scale may be too restricitive for some industries.

product firms are complements, or that marginal costs are negative (Tirole (1994)). In other words, observations with Lerner indexes lying outside the interval do not provide information on the degree of market power and, therefore, would bias results and turn them meaningless. Negative values, for instance, result either from losses or, for the case of the second measure, from corrected shares of material expenditures in operating substantially exceeding the coefficient of material. Excluding relevant observations is relevant, as firms with negative Lerner indexes also suffer from low productivity growth implying biased coefficients.

Vector X introduces control variables, capturing other drivers of technological progress and reorganization within firms. They are lagged by one period to overcome reverse causality (Franco & Marin (2017), Inui *et al.* (2012)). As productivity growth also responds to wage costs, labour market regulation and human capital, I involve logged firm-level average real wages (Del Bo (2013)). In comparison, Commins *et al.* (2011) employ shares of aggregate labour costs in value added and Franco & Marin (2017) logged industry-specific average wages, but they suffer from multicollinearity. Its lagged value serves as the demand shifter in the first stage. Data on firm-level wage costs are obtained from Orbis, deflated by country-level HCPIs sourced from Eurostat [12] and divided by firm-level employment. Its impact is ambiguous. Although more human capital allows firms to produce more efficiently and higher wage costs encourage capital substitution, higher wages may also signal inflexible and inefficient production processes. Depending on whether labour costs increase more or less strongly than labour productivity, the effect will be positive or negative.
Besides, following Castelnovo *et al.* (2019), Del Bo (2013) and Inui *et al.* (2012), I include the firm's logged real total assets to capture the effects of firm size. I expect a positive effect, as firm size represents an important driver of productivity growth (Inui *et al.* (2012)). Total assets are obtained from Orbis and deflated by the same price index as tangible fixed assets.

Furthermore, I include fixed effects for firms α_i, capturing unobserved firm-level heterogeneity (e.g. country, NACE industry, legal form). I also involve nested country-year dummies $D_c \cdot D_t$, capturing countrywide shocks (e.g. profit taxes, electricity and fuel prices, institutional quality, business activity), and three-digit NACE industry-year dummies dummies $D_s \cdot D_t$, controlling for industry-specific technological developments, propensities to innovate and European regulations (Hashmi (2013)).

Concerning endogeneity, three issues are worth discussing. First, endogeneity may be caused by reverse causality. Although Aghion *et al.* (2008) do not find strong instruments for inverted Lerner indexes and, therefore, treat them as exogeneous, I follow Inui *et al.* (2012) who employ lagged changes in the variable arguing that firms only respond to the level of competition but not to changes. Furthermore, companies are more likely to decide on the level of Lerner indexes by reorganizing production to affect efficiency growth than on the change in the same variables. To avoid burning too many observations due to involving too many lags, I use $\Delta LI_{i,t-1}$, as Inui *et al.* (2012) do in their baseline analysis, and the lagged difference in the squared Lerner indexes, $\Delta(LI^2)_{i,t-1}$. Second, I introduce important drivers of reorganization within firms, firm-level fixed

[12] https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de

effects and nested dummies to solve omitted variable biases implied by confounding factors. Owing to the chosen instruments, the first two observations of each firm are excluded. Third, output price biases still contaminate productivity and the Lerner indexes obtained from the production function, while input price biases can be avoided by introducing the demand shifter. Permanent measurement errors in productivity are eliminated by applying the productivity growth as the dependent variable in the second stage. Furthermore, the introduced firm-level fixed effects in the regression of productivity growth control for firm-specific trends in the underlying level of productivity, and for permanent measurement errors in the relevant Lerner index. Transient measurement errors, however, can be dealt with by using 2SLS.

3.2.2 Second proposition: industry-level productivity gaps rise with competition

To examine the second proposition, I first calculate the firm-specific gap between the firm's productivity and the productivity of the relevant three-digit NACE industry-country-specific leader (frontier), $TFP\,gap_{i,\,t} = \dfrac{max_{c,\,s,\,t}(TFP_{i,\,t}) - TFP_{i,\,t}}{max_{c,\,s,\,t}(TFP_{i,\,t})}$ (Atayde *et al.* (2021), Aghion *et al.* (2005)). [13] Afterwards, for every three-digit NACE industry-country-year combination, means of productivity gaps, Lerner indexes and firm-level characteristics are computed. Then, I estimate the same equation as in equation (3) at the country-industry-year-level substituting firm-level with three-digit NACE industry-country-level fixed effects and eliminating the square of the Lerner indexes. To compare my results with Inui *et al.* (2012), I also regress standard deviations of logged productivity computed at the same level. Although Inui *et al.* (2012) and Aghion *et al.* (2005) treat Lerner indexes as exogenous variables when examining this proposition, I use 2SLS using $\Delta LI_{i,t-1}$ as instrument in every specification and expect LI to negatively impact both dependent variables.

3.2.3 Third proposition: firms in competitive industries respond more sensitively to competition

When investigating the third proposition, industries have to be classified as leveled and unleveled sectors. Therefore, I follow Atayde *et al.* (2021) and compute the average of the industry-country specific productivity gaps $\overline{TFP\,gap}_{c,\,s,\,t}$, that are used as the dependent variable to assess the second proposition, for every country and year, $\overline{\overline{TFP\,gap}}_{c,\,t} = \dfrac{1}{S_{c,\,t}} \sum_{s_{c,\,t}=1}^{S_{c,\,t}} \overline{TFP\,gap}_{c,\,s,\,t}$. For a given year, a particular three-digit NACE industry-country combination is classified as leveled industry, if its gap is smaller than the annual average across industries, $neck-and-neck = 1\,if\,\overline{TFP\,gap}_{c,\,s,\,t} < \overline{\overline{TFP\,gap}}_{c,\,t}$. If the country-industry-specific gap is at least as large as the country-specific average, the same combination is defined as unleveled industry, $neck-and-neck = 0$. [14] Then, I re-estimate equation (3) for each type of industries separately,

[13] When using the 90^{th} or 99^{th} percentile instead of the maximum value, results of the empirical investigation of the second and third propositions, however, barely change.

[14] Results, however, are robust when using the country-specific median across country-industry-specific average gaps.

i.e.: one firm-level regression examining the concave relationship for leveled industries, and one for the unleveled industries (Inui *et al.* (2012)).

4 Results

In the first stage, I estimate production functions to construct productivity and Lerner indexes for every firm and year, while, in the second stage, I regress productivity growth using fixed effects models. Summary statistics are shown in *Table* 1.

Variable	Unit	Mean (SD)	Min - Med - Max	IQR (CV)
First Stage				
Real Operating Revenues	Mill. Euro	22.3 (168.2)	$0 < 3.0 < 14089.2$	8.8 (7.6)
Real Material Expenditures	Mill. Euro	13.5 (122.4)	$0 < 1.4 < 10179.1$	4.5 (9.0)
Real Tangible Assets	Mill. Euro	9.2 (1286.4)	$0 < 0.8 < 452504.6$	2.6 (140.5)
Number Employees	Integer	125.6 (333.3)	$1 < 38 < 15000$	109 (2.7)
Second Stage				
log(TFP)		4.5 (1.9)	$-26.1 < 4.4 < 12.5$	1.8 (0.4)
Δ log(TFP)		-0.0 (0.2)	$-11.2 < -0.0 < 5.8$	0.2 (-91.9)
Lerner Index (ROS)	Percent	0.3 (0.2)	$0.0 < 0.3 < 1.0$	0.2 (0.5)
Lerner Index (De Loecker & Warzynski)	Percent	0.3 (0.2)	$0.0 < 0.3 < 1.0$	0.3 (0.7)
HHI		0.1 (0.1)	$0.0 < 0.1 < 1.0$	0.1 (1.3)
CR4	Percent	0.4 (0.2)	$0.1 < 0.4 < 1.0$	0.4 (0.5)
Theil's L		1.0 (0.4)	$0.0 < 0.9 < 4.6$	0.5 (0.4)
Theil's S		1.0 (0.4)	$0.0 < 0.9 < 3.5$	0.5 (0.4)
Theil's T		1.0 (0.4)	$0.0 < 0.9 < 3.3$	0.5 (0.4)
Real Total Assets	Mill. Euro	7.0 (58.3)	$0.0 < 0.8 < 8512.2$	2.9 (8.3)
Average Real Wage	Thsnd. Euro	18.9 (170.7)	$0.0 < 14.2 < 48415.7$	10.2 (9.1)
High-Tech	Binary	0.3 (0.5)	$0.0 < 0.0 < 1.0$	1.0 (1.6)
Productivity Gap	Percent	0.7 (0.3)	$0 < 0.8 < 1.0$	0.3 (0.4)
SD of log(TFP)		0.4 (0.2)	$0.0 < 0.3 < 8.0$	0.2 (0.5)
Industry-Level Average Productivity Gap	Percent	0.7 (0.2)	$0.0 < 0.7 < 1.0$	0.3 (0.3)
Country-Level Average of Industry-Level Average Productivity Gap	Percent	0.5 (0.1)	$0.0 < 0.5 < 0.6$	0.0 (0.1)
Neck-and-Neck	Binary	0.2 (0.4)	$0.0 < 0.0 < 1.0$	0.0 (1.9)
Note:	'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, 'IQR' the interquartile range and 'CV' the coefficient of variation.			

Table 1: Descriptive statistics

4.1 Estimation of the production function

Tables I.1-I.5 in appendix I summarize the results of the production function estimations for each two-digit NACE industry-country combination. In every table, columns (1)-(3) provide the elasticities of output with respect to the considered inputs. Columns (4) and (5) display the numbers of observations and firms. The sum of input elasticities supplies an estimate of the degree of returns to scale. Therefore, column (6) shows the p-value of the Wald tests examining whether this sum significantly differs from one. Usually, the production function estimations consider attrition by introducing an additional stage into the estimation framework modelling the firms' entrance and exit behaviour. In some industries, too few firms exit the market not allowing to consider attrition. Column (7), thus, provides information on whether attrition can be and is considered or not. [15]

Overall, results are consistent with the literature (e.g. Richter & Schiersch (2017), Lu & Yu (2015), Du *et al.* (2014), Arnold *et al.* (2011)). Labour elasticities mostly vary between 0.20 and 0.40 (Richter & Schiersch (2017), Arnold *et al.* (2011)). In some industries, coefficients

[15] I exclude tobacco (C12) and coke and petroleum (C19) industries because of too few observations. Industries with less than 15 firms whose analysis does not allow to consider attrition are also dropped due to not-meaningful results.

lie between 0.05 and 0.20 as in Lu & Yu (2015) and Du *et al.* (2014). As in these studies, capital elasticities are usually small between 0 and 0.10. In Hungary, some of them, however, are larger, suggesting that the relevant industries produce more capital-intensively. Depending on the study, material elasticities vary between 0.40 and 0.90, confirming my results.
Nevertheless, there are some abnormalities. Particularly, one coefficients exceeds one (Hungary C21) and, similarly to Lu & Yu (2015), the elasticity of capital falls below zero in eleven combination (Austria C18, C25, C26, C28, C31 and C32; Hungary C16, C25, and C33; Slovakia C25 and C26).

Figures 1 and 2 show average Lerner indexes for two-digit NACE industries important to the Central European core. Average return on sales-style Lerner indexes are quite stationary fluctuating around 0.33. Although Lerner indexes obtained from the production function take on similar values, they seem to develop in the opposite direction in some industries. When not correcting the shares of material expenditures for fluctuations in output unrelated to variations in inputs, these, however, exhibit similar developments, as they also include such variations which are completely reflected by the return on sales highlighting the importance of the correction.

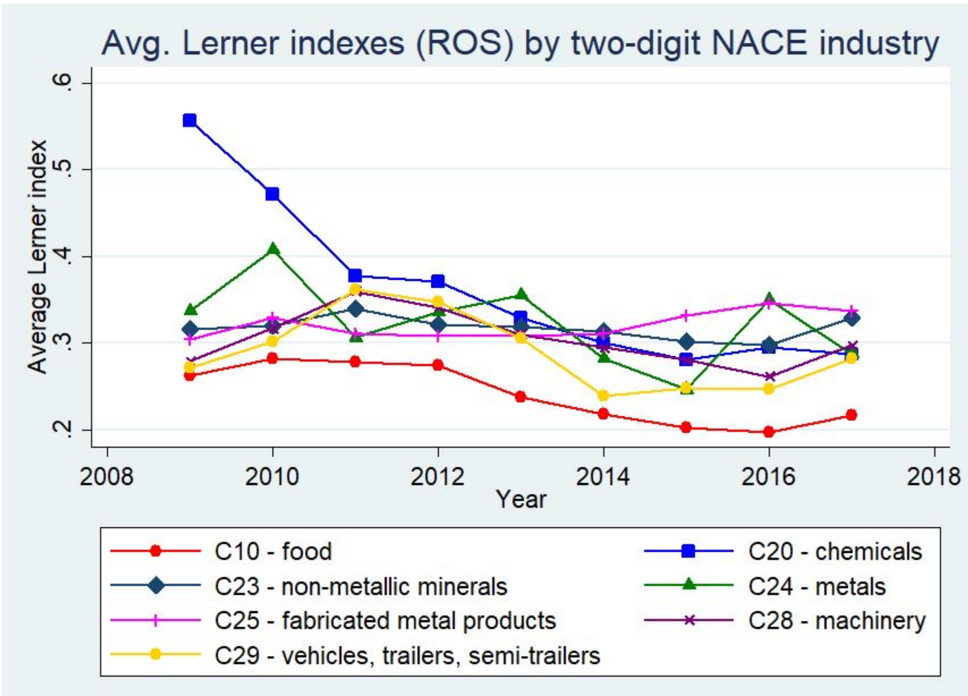

Figure 1: Average Lerner indexes (ROS) by two-digit NACE industry

4.2 Effects of market concentration on productivity growth

4.2.1 First proposition

Table 2 displays the estimates of equation (3) used to examine the model's first proposition. Column (1) shows the results of the regressions using the return on sales-definition of the Lerner index, while column (2) provides the analogous for the one introducing the Lerner index obtained

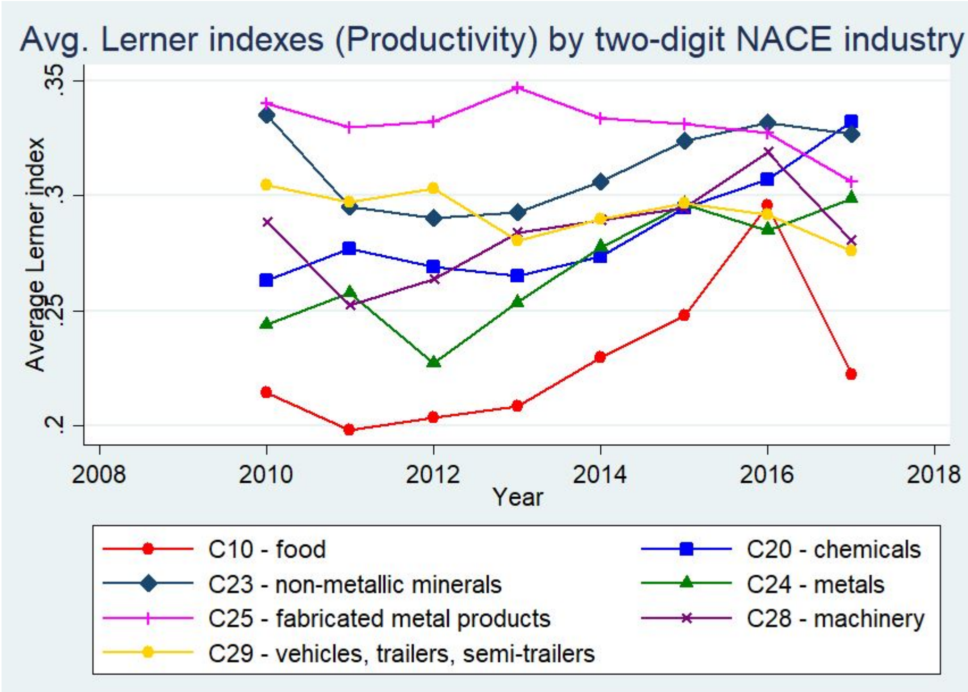

Figure 2: Average Lerner indexes (Productivity) by two-digit NACE industry

from the production function estimates. Standard errors are clustered at the firm-level to overcome residual serial correlation. [16] In all the columns, underidentification, weak-identification tests and endogeneity tests are satisfied. [17]

Confirming the literature (e.g. Hashmi (2013), Inui *et al.* (2012), Aghion *et al.* (2005)), relationships between market concentration and productivity growth are inverted-u shaped. Concerning interpretation, suppose the following example. In column (1), an increase of the Lerner-Index, starting from 0.30 ($\sim$ mean, median), by one percentage point decreases productivity growth by 2.8 percentage points. In column (2), productivity growth declines by 0.8 percentage points. Productivity growth maximizing Lerner indexes are identified by taking first-order derivatives, setting them equal to zero and solving for LI. In column (1), the productivity growth maximizing Lerner index lies around 0.107, while in column (2) the same value equals 0.159. Hashmi (2013), Inui *et al.* (2012) and Aghion *et al.* (2005) find optimizing values around 0.95 when using inverted Lerner indexes, $1 - LI$. The inverses of my optimizing values are 0.893, being consistent with these studies, and 0.841. The latter is smaller, because underlying Lerner indexes are calculated from material shares corrected for variations in output unrelated to fluctuations in inputs (e.g. elasticities of demand, income level). In comparison, the return on sales

[16] To check whether results are driven by industries with abnormal production function estimates, I exclude relevant industry-country combinations, but they, however, barely change. Since the numbers of firms are large in industries C25 and C28, results may be driven by these sectors. To check sensitivity, I run one regression excluding both industries and one regression only for these sectors. As all regressions show concave relationships, I can rule out that results are driven by this issue.

[17] The critical values by Stock-Yogo have to be interpreted with caution, as they actually refer to Cragg-Donald Wald F statistic that assumes i.i.d. errors and can only be tabulated for up to three endogenous variables. Alternatively, the Kleibergen-Paap rk Wald F statistic can be cautiously compared with the 'rule of thumb' by Staiger & Stock (1997). The results do not suffer from weak instruments, if the F statistics on the joint significance of the instruments in the first stage regressions exceed ten (Baum *et al.* (2007)).

completely reflects them given its formula. It follows an upwards biased optimal Lerner indexes highlighting the importance of the correction (De Loecker & Warzynski (2012)). This can be seen from a regression on the Lerner indexes whose underlying share of material expenditure is not corrected providing optimizing values around 0.98 closely to 0.95.
Besides, the values by Hashmi (2013) and Aghion *et al.* (2005), however, stem from regressions of numbers of patents, while Inui *et al.* (2012) regress the growth rates of efficiency derived by DEA. Another important reason is that these studies employ data on almost all industries of the analysed countries, while my dataset only covers manufacturing sectors, as estimating production functions for services is not common in the literature. Therefore, escape-competition effects are plausibly stronger in manufacturing than in other sectors (e.g. services that make up the largest parts of nowadays economies) due to its special characteristics. Manufacturing industries represent the main driver of technological progress (Baumol (1967)) and, therefore, produce more research-intensively than service sectors, i.e.: to escape competition, manufacturing companies must develop new products, which is costly and, thus, larger markups are required to cover the high research costs. Furthermore, four out of five countries are post-communist having transitioned from centrally planned to market economies, although the government's role is still pervasive. Particularly, socialist planning supported large monopolies by missallocating resources. Poorly implemented privatisations did not create contestable markets, but established legal monopolies fostering market barriers (Buccirossi & Ciari (2018)). As the studies discussed analyse developed economies (e.g. UK, USA, Japan) characterized by well-functioning markets, derived efficiency growth maximizing inverted Lerner indexes are plausibly higher. As analysed post-communist countries still suffer from strong market barriers and not perfectly-working markets, optimizing values will take on higher values. They investigate different time horizons (1997-2003, 1973-1994). Next, I also cover smaller firms. Unlike Inui *et al.* (2012), I follow Aghion *et al.* (2005) and employ contemporaneous Lerner indexes instead of the values lagged by one period. Differences also result from different instruments. Analogous to Inui *et al.* (2012), I involve the lagged first differences in market concentration as instruments, because regularly used instruments (e.g. import shares, firm numbers, antitrust penalties) lack instrument relevance as in Aghion *et al.* (2008). Instead of using first differences lagged by multiple periods as instruments, I employ the first differences in the Lerner indexes and their squares. Last, unlike these studies, I include a large set of nested dummies to avoid omitted variable biases.

As expected, firm size, as measured by logged real total assets, significantly increases productivity growth (Inui *et al.* (2012)). An increase by one percent raises the productivity growth rate by 0.018-0.025 percentage points. Conversely, average real wages per employee significantly decrease productivity growth. A rise by one percent drops the dependent variable by 0.213-0.220 percentage points.

To verify robustness, I re-estimate the models using country-industry-specific measures of market concentration popular in the literature: Herfindahl-Hirschman index (HHI), CR4, and Theil indexes (Atayde *et al.* (2021), Opoku *et al.* (2020), Lu & Yu (2015), Inui *et al.* (2012)). Variables are discussed and results are shown in appendix J. Again, contemporary market concentration is instrumented with lagged first differences. Despite the strong instruments, HHI

	Dependent Variable: $\Delta log(TFP)$	
	Lerner index (ROS)	Lerner index (Productivity)
	(1)	(2)
Lerner index$_t$	1.536 ∗ ∗	0.939 ∗ ∗∗
	(0.662)	(0.355)
Squared lerner index$_t$	−7.166 ∗ ∗∗	−2.962 ∗ ∗∗
	(1.236)	(0.562)
Log(real total assets$_{t-1}$)	0.018 ∗ ∗∗	0.025 ∗ ∗∗
	(0.006)	(0.006)
Log(average real wage$_{t-1}$)	−0.220 ∗ ∗∗	−0.213 ∗ ∗∗
	(0.013)	(0.015)
R-squared	−3.233	−0.455
Observations	75776	42498
Units	13951	9767
Underidentification		
Kleibergen-Paap rk LM statistic	174.665	531.314
p-value	0.000	0.000
Weak identification		
Cragg-Donald Wald F statistic	863.586	637.486
Kleibergen-Paap rk Wald F statistic	82.775	292.348
Stock-Yogo weak ID test critical values		
10% maximal IV size	7.03	7.03
15% maximal IV size	4.58	4.58
20% maximal IV size	3.95	3.95
25% maximal IV size	3.63	3.63
Endogeneity		
Endogeneity test	996.286	80.413
p-value	0.000	0.000
Firm-FE	*yes*	*yes*
Country-year dummies	*yes*	*yes*
Industry-year dummies	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the firm-level. Variance inflation factors (VIFs) are computed manually from the within-R2s of fixed effects regressions of each covariate on the other covariates, firm-level fixed effects and nested country-year and industry-year dummies, using the data from 2010 to 2017. Observations of 2009 are dropped due to the lagged variables. VIFs of the controls, sligthly exceeding one, do not suggest multicollinearity. On the other hand, the VIFs of the Lerner indexes vary between 5.75 and 7.55 due to the inclusion of its squared term suggesting multicollinearity, but decrease severely when excluding its square. *p<0.1; **p<0.05; ***p<0.01	

Table 2: Results of examination of first proposition

and CR4 are exogenous as suggested by the endogeneity tests. Therefore, the relevant columns provide the results of the fixed effects regressions. All the columns display the concave relationship between market concentration and productivity growth, although both coefficients are only significant for Theil's S and T indexes. For the other regressions, standard errors might be inflated too much by multicollinearity, resulting in partially insignificant coefficients.

Another interesting aspect whether responses differ across high-tech and low-tech industries. To examine this issue, I perform regressions separately for these types of industries. Industries are classified using the definition of the EU Commission. [18] In *Table* K.1, I use the definition based on the two-digit NACE industries, but results are robust when employing the classification based on three-digit NACE industries. When involving the return on sales, productivity growth maximizing Lerner indexes are higher in high-tech industries and smaller in low-tech industries suggesting that high-tech industries require higher markups to cover research costs. However, in the regressions introducing the Lerner indexes obtained from the production function the results turn to the opposite again highlighting the importance of the correction. Hence, Schumpeterian effects now dominate in high-tech industries that are plausibly often characterized by few market leaders, while escape-competition effects dominate in low-tech industries in which competition is stronger due to larger firm numbers. When using the return on sales, the higher optimizing value in high-tech industries might, therefore, result from changes in income.

[18] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

4.2.2 Second proposition

Table 3 shows the results of country-three-digit NACE industry-specific fixed effects regressions. Columns (1) and (2) provide the outcomes of the regressions employing the average gaps to the frontier as dependent variables, while columns (3) and (4) display the analogous for the ones using the standard deviations of logged firm-level productivity. Columns (1) and (3) show the results when using the first definition of the Lerner index, while columns (2) and (4) provide the same for the second definition.

The results are partially consistent with Inui *et al.* (2012) and Aghion *et al.* (2005). As in both studies, the return on sales-style Lerner index has negative effects, suggesting that competition indeed widens the industry-specific average gap to its frontier and productivity dispersion. Nevertheless, both coefficients are insignificant. An increase of the average Lerner index by one percentage point decreases the average gap by 0.025 and the standard deviation by 0.581 percentage points. Conversely, Lerner indexes calculated from the production function significantly increases the dependent variables, suggesting that the positive effect of wiping out inefficient firms dominates the negative effect of falling innovation rates. Despite the sufficiently strong instruments, endogeneity tests suggest the potentially endogenous Lerner indexes to be exogenous. Therefore, columns (2) and (4) present the results of the fixed effects regressions. In comparison, both studies classify Lerner indexes as exogenous variables suggesting that lacking endogeneity might not be a major issue at the industry-country-level regressions. Nevertheless, the conclusions are in line with Hashmi (2013) who also finds mixed results. A rise of the average Lerner index by one percentage point significantly raises the average gap by 0.267 and the standard deviation by 0.541 percentage points.

	Dependent Variable:			
	Average Gap to Frontier		*Standard Deviation of log(TFP)*	
	Lerner index (ROS)	Lerner index (Productivity)	Lerner index (ROS)	Lerner index (Productivity)
	(1)	(2)	(3)	(4)
Lerner index$_t$	−0.025	0.267∗∗∗	−0.581	0.541∗∗∗
	(0.184)	(0.080)	(0.393)	(0.131)
Log(real total assets$_{t-1}$)	−0.012∗∗∗	−0.010∗∗	−0.014∗∗	−0.015∗∗
	(0.003)	(0.004)	(0.007)	(0.006)
Log(average real wage$_{t-1}$)	−0.018	0.001	−0.078	−0.015
	(0.021)	(0.041)	(0.055)	(0.057)
R-squared	0.005	0.342	−0.055	0.438
Observations	2610	1996	2518	1968
Units	425	394	408	386
Underidentification				
Kleibergen-Paap rk LM statistic	69.010		71.582	
p-value	0.000		0.000	
Weak identification				
Cragg-Donald Wald F statistic	148.370		141.043	
Kleibergen-Paap rk Wald F statistic	63.782		66.750	
Stock-Yogo weak ID test critical values				
10% maximal IV size	16.38		16.38	
15% maximal IV size	8.96		8.96	
20% maximal IV size	6.66		6.66	
25% maximal IV size	5.53		5.53	
Endogeneity				
Endogeneity test	3.785		7.925	
p-value	0.052		0.005	
Country-industry-FE	*yes*	*yes*	*yes*	*yes*
Country-year dummies	*yes*	*yes*	*yes*	*yes*
Industry-year dummies	*yes*	*yes*	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the country-industry-level. Variance inflation factors (VIFs) are computed manually from the within-R2s of fixed effects regressions of each covariate on the other covariates, firm-level fixed effects and nested country-year and industry-year dummies, using the data from 2011 to 2017. Observations of 2009 and 2010 are dropped due to the specification of the production function and lagged variables. VIFs of the covariates, varying between 1.76 and 4.11, do not suggest multicollinearity. *p<0.1; **p<0.05; ***p<0.01			

Table 3: Results of examination of second proposition

4.2.3 Third proposition

Table 4 provides the results of the examination of the third proposition. Columns (1) and (3) show the regressions using the first definition of the Lerner index, while columns (2) and (4) display the same for the second definition. Columns (1) and (3) provide the regression results for the leveled industries, whereas columns (2) and (4) show the analogous for unleveled industries. The conclusions are consistent with Inui *et al.* (2012) and Aghion *et al.* (2005). In both specifications, the productivity growth maximizing level of market concentration is larger in leveled industries, while in unleveled industries the coefficients are almost the same as in the entire manufacturing sector, as shown in *Table* 2. In other words, the productivity growth maximizing level of competition in leveled industries is smaller than in unleveled industries, as proposed by the model by Aghion *et al.* (2005). In comparison to Inui *et al.* (2012), coefficients stay significant in unleveled industries, favouring the conclusions by Aghion *et al.* (2005). In leveled industries, productivity growth maximizing Lerner indexes equal 0.155 and 0.159, while, in unleveled industries, they are 0.098 and 0.154. The relevant inverted values of the leveled industries, therefore, are 0.845 and 0.841. In comparison, the ones by Inui *et al.* (2012) and Aghion *et al.* (2005) are between 0.90 and 0.94. In the regression employing the Lerner indexes by De Loecker & Warzynski (2012) the change in the optimizing value is as small as in the mentioned studies ($\sim$ 1%), while in the regression applying the return on sales as in these studies the change in the inverted optimizing value is larger ($\sim$ 5%) which is due to the applied methods to obtain efficiency, dependent variables and sampled firms and countries. For instance, these studies analyse all industries of the given countries, while my dataset only covers manufacturing sectors affecting the classification of country-industry pairs, as estimating production functions for services is not common in the literature.

	Dependent Variable: $\Delta log(TFP)$			
	Level Lerner index (ROS) (1)	Unlevel Lerner index (ROS) (2)	Level Lerner index (Productivity) (3)	Unlevel Lerner index (Productivity) (4)
Lerner index$_t$	3.234	1.546*	0.994	1.004**
	(2.192)	(0.821)	(1.015)	(0.419)
Squared lerner index$_t$	−10.411***	−7.851***	−3.119*	−3.269***
	(3.889)	(1.557)	(1.630)	(0.671)
Log(real total assets$_{t-1}$)	0.033**	0.015**	0.025	0.024***
	(0.014)	(0.007)	(0.017)	(0.007)
Log(average real wage$_{t-1}$)	−0.215***	−0.223***	−0.173***	−0.212***
	(0.026)	(0.016)	(0.042)	(0.015)
R-squared	−4.069	−3.898	−0.527	−0.562
Observations	13936	59387	7222	33437
Units	3506	11878	2215	8176
Underidentification				
Kleibergen-Paap rk LM statistic	40.091	123.420	60.934	449.374
p-value	0.000	0.000	0.000	0.000
Weak identification				
Cragg-Donald Wald F statistic	88.816	612.872	64.711	446.221
Kleibergen-Paap rk Wald F statistic	19.104	58.164	30.888	233.807
Stock-Yogo weak ID test critical values				
10% maximal IV size	7.03	7.03	7.03	7.03
15% maximal IV size	4.58	4.58	4.58	4.58
20% maximal IV size	3.95	3.95	3.95	3.95
25% maximal IV size	3.63	3.63	3.63	3.63
Endogeneity				
Endogeneity test	270.964	754.067	17.891	70.268
p-value	0.000	0.000	0.000	0.000
Firm-FE	*yes*	*yes*	*yes*	*yes*
Country-year dummies	*yes*	*yes*	*yes*	*yes*
Industry-year dummies	*yes*	*yes*	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the firm-level.			
				*p<0.1; **p<0.05; ***p<0.01

Table 4: Results of examination of third proposition

4.3 Discussion

The overriding goal of competition policy is to ensure competitive environments and avoid the rise of monopolies. Although competition represents an important driver of productivity growth and innovation, too high levels may discourage corporate innovation and reorganization, making it difficult to competition authorities to decide on how much market concentration to allow. This study sheds light on the impacts of market concentration on firm performance. After estimating production functions, obtained productivity growth rates and associated measures are regressed on Lerner indexes to assess the relationship between efficiency growth and competitive pressure. I add to the literature by employing Lerner indexes estimated by De Loecker & Warzynski (2012).

Overall, my results support the theoretical model by Aghion *et al.* (2005) and related empirical studies (e.g. Inui *et al.* (2012), Tingvall & Poldahl (2006)). The results support the concave relationship between competition and productivity growth. Furthermore, firms in competitive industries respond more strongly to competition. Last, competition does not necessarily widen country-industry-specific gap to the efficiency frontier. In comparison, productivity growth maximizing Lerner indexes are plausibly larger, as relevant countries are either post-communist still suffering from strong market barriers, legal monopolies, pervasive roles of the state, and not perfectly-working markets, or belong to the Central European manufacturing core. In this region structural shifts to service industries are less pronounced or even reversed. Another takeaway relates to the difference between return on sales and Lerner indexes derived by De Loecker & Warzynski (2012). While the first measure completely reflects variations in output unrelated to fluctuations in inputs, material shares used to obtain Lerner indexes from the production functions excludes them. It follows an upwards bias of the inverted optimal Lerner indexes.

One set of econometric issues is implied by the instruments' nature. Since $\Delta LI_{i,t-1}$ is included in $LI_{i,t}$, instruments might lack exogeneity causing inconsistent estimates. Nevertheless, chosen instruments are strong reducing the bias and provide informative conclusions even under noteworthy deviations from the exclusion restriction (Conley *et al.* (2012), Wooldridge (2010)). Conversely, other studies (e.g. Hashmi (2013), Aghion *et al.* (2008)) either use weak ones or treat Lerner indexes as exogenous variables due to the lack of strong instruments, suffering from stronger inconsistency. Particularly, the need for IVs is illustrated by treating Lerner indexes as exogenous variables as in Aghion *et al.* (2008). Similarly, the relevant regressions suggest convex relationships rejecting the theoretical model. Thus, applying strong, though not completely exogenous, IVs implies smaller biases and, therefore, is superior.

Moreover, output price biases still contaminate estimated productivity and Lerner indexes by De Loecker & Warzynski (2012). When regressing productivity growth on this Lerner index, the dependent and the independent variable, suffer from the same type of measurement error. In other words, measurement errors correlate. In this case, the assumption of IV exogeneity will not be satisfied. Alternative estimators (e.g. Ronning & Rosemann (2008), Schaalje & Butts (1993)), however, do not consider the simultaneity between the dependent and explanatory variable. Thus, I still prefer 2SLS over them (Ronning & Rosemann (2008)). On the other hand, Day *et al.*

(2004) show that biases are small, when measurement errors are weakly correlated (below 0.7) and the explanatory variable is exogenous. Although Lerner indexes are endogenous, correlation will not be large. First, calculating the growth rate already drops permanent measurement errors in the dependent variable. Second, the firm-level fixed effects control for firm-level trends in the growth of the measurement error. Third, they also capture permanent measurement errors in the Lerner index. Summing up, if there should still be correlation, it will be small suggesting only mild biases.

The last set of econometric issues concerns the Lerner index obtained using De Loecker & Warzynski (2012) and relates to the previous issue. As Bond *et al.* (2021) show that when imposing the demand system by Hall (1986) assuming identical own-price elasticities and cross-price elasticities of zero, then the obtained Lerner indexes should be zero for every firm and year under the correct model specification. Thus, estimated markups do not provide any information on the true ones. However, in models with heterogeneous markups (e.g. Klenow & Willis (2016), Atkeson & Burstein (2008), Kimball (1995)) own-price demand elasticities vary across firms and, therefore, at least one firm exhibits a markup differing from one. In this case, the estimator is the sum of the averaged true markup and a weighted average of the demand elasticities of the firms sharing the same production function. Thus, the estimator is informative, as the true markup and the estimator are correlated. As the applied method does not impose assumptions on the underlying demand system, the second case should be more likely to be true.

5 Conclusion

Whether competition spurs or curbs innovation and productivity growth is a crucial issue for Central European manufacturing sectors due to the decline of productivity growth since the financial crisis and the fact that competition represents an important driver in economic growth. I investigate the effects of market concentration on firm performance not only to provide policy lessons for designing competition policies, but also contribute to the literature by applying an alternative approach to compute Lerner indexes. Therefore, in the first stage, Cobb-Douglas production functions are estimated with the algorithm by Ackerberg *et al.* (2015), using data on Central European manufacturing firms, from 2009 to 2017. In the second stage, I estimate the non-linear impacts of market concentration on productivity growth with fixed effects models considering endogeneity.

The results show that relationships between competition and productivity growth are indeed concave, supporting the empirical findings and the theoretical model by Aghion *et al.* (2005). Furthermore, firms in competitive industries respond more strongly to competition, confirming another proposition of the model. Conversely, I do not find unambiguous evidence for the proposition of a positive impact of competition on country-industry-specific average productivity gaps. In comparison, productivity growth maximizing Lerner indexes are plausibly larger, as relevant countries are either post-communist still suffering from strong market barriers, legal monopolies, pervasive roles of the state, and not perfectly-working markets, or belong to the

Central European manufacturing core in which the structural shift to service industries is less pronounced or even reversed. Policy makers should consider the concave relationship between competition and productivity growth when deciding on how much market concentration to allow. Generally, I recommend to continue liberalizing and eliminating market barriers to promote competition in concentrated industries. Additionally, I suggest to carefully reform patent law in the case it should be too restrictive and discourages innovation (e.g. pharmaceutical products). To spur innovation in competitive industries, I also suggest to raise research grants that also benefits high-tech sectors, implement tax privileges favouring long-run investments in these firms (e.g. venture capital companies) and implement and provide legal frameworks for alternative financing models (e.g. crowd funding).

Appendices

G The method by Ackerberg/Caves/Frazer

When estimating production functions, much consideration needs to be given to identification problems. First, simultaneity biases arise because of the endogeneity of inputs, i.e.: firms with positive productivity shocks demand larger input amounts. Hence, inputs correlate with unobserved productivity. Second, attrition in the data causes identification problems, because firms with high productivity levels have a higher probability to survive, while firms with low levels of productivity are more likely to exit the market (Levinsohn & Petrin (2003), Olley & Pakes (1996), Marschak & Andrews (1944)).

Unlike Olley & Pakes (1996) and Levinsohn & Petrin (2003), Ackerberg *et al.* (2015) allow for a dynamic specification in the choice of labour by claiming that labour also depends on unobserved productivity. In other words, it assumes that labour is chosen prior to other flexible inputs, or is dynamic and subject to adjustment costs. Hence, the coefficients of free variables (e.g. labour) cannot be correctly identified in the first stages of Olley & Pakes (1996) and Levinsohn & Petrin (2003). Instead, the coefficients are estimated in the second stage. To get the intuition, imagine a subperiod between periods $t-1$ and t. First, the firm chooses the optimal amount of material. Second, the productivity shock occurs in the subperiod. Third, the amount of labour is purchased. Now, labour is an element of the demand function for material in period t, which is still invertible as long as m is strictly increasing in productivity.

In the first stage, I run

$$y_{i,t} = \phi_{i,t}(l_{i,t}, k_{i,t}, m_{i,t}) + \psi_{i,t} \tag{G.1}$$

to obtain estimates for the expected output $\hat{\phi}_{i,t}$ and the productivity shock $\hat{\psi}_{i,t}$. The expected output is

$$\phi_{i,t} = \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \beta_m \cdot m_{i,t} + h_t^{-1}(m_{i,t}, k_{i,t}) \tag{G.2}$$

with $h^{-1}(.)$ being the inverted demand for material (proxy variable). Assuming that the demand for material is strictly monotonically increasing in productivity allows to invert the demand function to obtain productivity as a function of the proxy and state variables. Then, unobserved productivity ω is substituted with the inverted function, giving equation (G.2).

In the second stage, estimates for all production function coefficients $\beta = (\beta_k, \beta_l, \beta_m)$ are calculated by relying on the law of motion of productivity

$$\omega_{i,t} = g_t(\omega_{i,t-1}, a_{i,t-1}) + \xi_{i,t} \tag{G.3}$$

using equation (G.4). a is the demand shifter that affects the demand for material m, but does not directly enter the production function as an input.

$$\omega_{i,t}(\beta) = \phi_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \beta_m \cdot m_{i,t} \tag{G.4}$$

Non-parametrically regressing $\omega(\beta)$ on its lag recovers the innovations to productivity ξ, required to form moment conditions, used to estimate the coefficients β with GMM. To obtain the standard errors of β, I rely on cluster bootstrapping.

H The method by De Loecker and Warzynski

To obtain markups, suppose the following production function. Y denotes the level of output, K capital, L employment, M material and ζ the sum of unobserved productivity and the productivity shock. Again, indices i and t represent firms and years.

$$Y_{i,t} = Y_{i,t}(K_{i,t}, L_{i,t}, M_{i,t}, \zeta_{i,t}) \tag{H.1}$$

Assuming that active firms minimize costs allows to formulate the associated Lagrangian function with r, w, p_M and λ being the interest rate, wage, material price and Lagrange multiplier.

$$\mathcal{L} = r_{i,t} \cdot K_{i,t} + w_{i,t} \cdot L_{i,t} + p_{M,i,t} \cdot M_{i,t} + \lambda_{i,t} \cdot (Y_{i,t} - Y_{i,t}(\cdot)) \tag{H.2}$$

The first-order condition for any input free of adjustment costs (in this case material) is described in equation (H.3). Given the cost minimization problem, the Lagrangian multiplier equals the marginal costs of production c.

$$\frac{\partial \mathcal{L}}{\partial M_{i,t}} = p_{M,i,t} - \lambda_{i,t} \cdot \frac{\partial Y_{i,t}(\cdot)}{\partial M_{i,t}} = 0 \tag{H.3}$$

Rearranging equation (H.3) and multiplying both sides with $\frac{M_{i,t}}{Y_{i,t}}$ generates equation (H.4) implying that cost minimization requires the firm to equalize the output elasticity of material with the right-hand side of the equation.

$$\underbrace{\frac{\partial Y_{i,t}}{\partial M_{i,t}} \cdot \frac{M_{i,t}}{Y_{i,t}}}_{\beta_m} = \frac{1}{\lambda_{i,t}} \cdot \frac{p_{M,i,t} \cdot M_{i,t}}{Y_{i,t}} \tag{H.4}$$

Next, the expression for the price-cost margin $\mu_{i,t} = \frac{P_{Y,i,t}}{\lambda i,\, t}$, which is robust to various static price setting models and does not require any assumptions on the particular form of price competition between firms, is plugged in into equation (H.4). Nevertheless, this assumes that companies set prices every period ruling out dynamics in pricing. In comparison, a full profit maximisation problem may also be considered. Nonetheless, cost minimization problems are part of profit maximisation problems and, therefore, suffice to derive price-cost margins. Furthermore, profit maximisation requires to introduce additional assumptions (e.g. type of competition) substantially raising complexity (Koppenberg & Hirsch (2021), Basu (2019), De Loecker & Warzynski (2012)). Now, the output elasticity of material equals the price-cost margin times the share of nominal material expenditures in nominal revenue θ computable from the data. As in De Loecker & Warzynski (2012), I correct θ for fluctuations stemming from variations in output unrelated to variables impacting input demand by multiplying it with the exponentiated productivity shock from the first stage $e^{\psi_{i,t}}$.

$$\beta_m = \mu_{i,t} \cdot \underbrace{\frac{p_{M,i,t} \cdot M_{i,t}}{p_{Y,i,t} \cdot Y_{i,t}}}_{\theta_{i,t}} \tag{H.5}$$

Last, solving for the price-cost margin and plugging the resulting identity into the equation of the Lerner index LI gives

$$\begin{aligned} LI_{i,t} &= \frac{p_{Y,i,t} - c_{i,t}}{p_{Y,i,t}} \\ &= 1 - \frac{c_{i,t}}{p_{Y,i,t}} \\ &= 1 - \frac{1}{\mu_{i,t}} \end{aligned} \tag{H.6}$$

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.394*** (0.000)	0.036*** (0.000)	0.566*** (0.000)	270	79	0.00	*yes*
C11 beverages	*NA* *NA*	*NA* *NA*	*NA* *NA*	38	12	*NA*	*no*
C13 textiles	0.245** (0.100)	0.062** (0.031)	0.662** (0.276)	67	21	0.92	*yes*
C14 wearing apparel	*NA* *NA*	*NA* *NA*	*NA* *NA*	16	8	*NA*	*no*
C15 leather	*NA* *NA*	*NA* *NA*	*NA* *NA*	21	6	*NA*	*no*
C16 wood products	0.383*** (0.000)	0.160*** (0.000)	0.443*** (0.000)	140	41	0.00	*no*
C17 paper and pulp products	0.196*** (0.000)	0.045*** (0.000)	0.805*** (0.000)	106	27	0.00	*no*
C18 printing and recorded media	0.618*** (0.206)	−0.382* (0.215)	0.681*** (0.213)	73	23	0.84	*no*
C20 chemicals and chemical products	0.454 (0.397)	0.032 (0.076)	0.298 (0.572)	161	49	0.82	*no*
C21 pharmaceutical products	0.255*** (0.077)	0.019 (0.019)	0.804*** (0.246)	66	20	0.81	*yes*
C22 rubber and plastics products	0.262*** (0.000)	0.038*** (0.000)	0.673*** (0.000)	152	48	0.00	*no*
C23 other non-metallic mineral products	0.206 (0.171)	0.054 (0.058)	0.694 (0.572)	170	50	1.00	*yes*
C24 basic metals	0.263*** (0.082)	0.082*** (0.025)	0.621*** (0.193)	215	57	0.92	*yes*
C25 fabricated metal products	0.552*** (0.044)	−0.006 (0.016)	0.453*** (0.037)	314	96	1.00	*yes*
C26 computer, electronic, optical products	2.548*** (0.692)	−0.169** (0.083)	0.250*** (0.033)	165	53	0.04	*yes*
C27 electrical equipment	0.221*** (0.012)	0.036 (0.024)	0.691*** (0.005)	126	36	0.10	*yes*
C28 machinery	0.405*** (0.020)	−0.011 (0.077)	0.595*** (0.057)	403	119	0.75	*yes*
C29 motor vehicles, trailers, semi-trailers	0.411 (0.498)	0.017 (0.020)	0.606 (0.728)	111	34	1.00	*no*
C30 other transport equipment	*NA* *NA*	*NA* *NA*	*NA* *NA*	24	8	*NA*	*no*
C31 furniture	0.351** (0.138)	−0.014 (0.010)	0.640** (0.252)	41	12	1.00	*yes*
C32 other manufacturing	0.636 (0.953)	−0.016 (0.140)	0.397 (0.742)	46	18	1.00	*yes*
C33 repair, installation	0.793*** (0.191)	0.087** (0.042)	0.273*** (0.105)	44	15	0.45	*no*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table I.1: Results of production function estimation for Austria

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.112*** (0.000)	0.090*** (0.000)	0.763*** (0.000)	4,153	679	0.00	*yes*
C11 beverages	0.163*** (0.015)	0.112** (0.049)	0.788*** (0.021)	756	123	0.02	*yes*
C13 textiles	0.317*** (0.000)	0.118*** (0.000)	0.525*** (0.000)	1,058	174	0.00	*yes*
C14 wearing apparel	0.311*** (0.048)	0.041 (0.029)	0.621*** (0.096)	689	125	0.86	*yes*
C15 leather	0.440*** (0.005)	0.071** (0.033)	0.499*** (0.010)	228	39	0.58	*yes*
C16 wood products	0.219*** (0.004)	0.070*** (0.016)	0.671*** (0.004)	2,042	337	0.00	*yes*
C17 paper and pulp products	0.230*** (0.002)	0.040*** (0.014)	0.752*** (0.008)	991	159	0.00	*yes*
C18 printing and recorded media	0.372*** (0.010)	0.030 (0.024)	0.516*** (0.009)	1,132	180	0.00	*yes*
C20 chemicals and chemical products	0.191*** (0.000)	0.153*** (0.000)	0.599*** (0.000)	1,451	211	0.00	*yes*
C21 pharmaceutical products	0.196*** (0.011)	0.097*** (0.034)	0.725*** (0.014)	303	42	0.45	*no*
C22 rubber and plastics products	0.282*** (0.000)	0.053*** (0.000)	0.673*** (0.000)	4,264	646	0.00	*yes*
C23 other non-metallic mineral products	0.213*** (0.012)	0.072*** (0.019)	0.717*** (0.009)	2,217	342	0.89	*yes*
C24 basic metals	0.242*** (0.010)	0.048* (0.025)	0.685*** (0.004)	1,099	173	0.19	*yes*
C25 fabricated metal products	0.296*** (0.000)	0.074*** (0.000)	0.583*** (0.000)	10,249	1,683	0.00	*yes*
C26 computer, electronic, optical products	0.343*** (0.004)	0.050*** (0.012)	0.610*** (0.006)	1,506	232	0.11	*yes*
C27 electrical equipment	0.354*** (0.004)	0.053*** (0.020)	0.555*** (0.005)	3,160	492	0.00	*yes*
C28 machinery	0.284*** (0.003)	0.048*** (0.010)	0.645*** (0.006)	6,218	940	0.00	*yes*
C29 motor vehicles, trailers, semi-trailers	0.350*** (0.000)	0.040*** (0.000)	0.625*** (0.000)	2,337	357	0.00	*yes*
C30 other transport equipment	0.256*** (0.015)	0.006 (0.047)	0.695*** (0.010)	636	95	0.09	*yes*
C31 furniture	0.177*** (0.023)	0.058 (0.038)	0.726*** (0.047)	1,326	219	0.13	*yes*
C32 other manufacturing	0.315*** (0.013)	0.074** (0.031)	0.582*** (0.015)	1,289	216	0.12	*yes*
C33 repair, installation	0.431*** (0.010)	0.014 (0.021)	0.527*** (0.008)	2,896	486	0.00	*yes*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table I.2: Results of production function estimation for Czech Republic

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.190*** (0.010)	0.030 (0.067)	0.666*** (0.032)	2,269	369	0.00	*yes*
C11 beverages	0.397*** (0.014)	0.040 (0.084)	0.636*** (0.027)	465	78	0.11	*yes*
C13 textiles	0.362*** (0.014)	0.087*** (0.018)	0.551*** (0.011)	234	43	1.00	*yes*
C14 wearing apparel	0.391*** (0.010)	0.077** (0.039)	0.340*** (0.034)	261	43	0.00	*yes*
C15 leather	0.299*** (0.012)	0.104 (0.082)	0.529*** (0.037)	143	22	0.07	*yes*
C16 wood products	0.232* (0.139)	−0.018 (0.042)	0.725** (0.352)	349	64	0.89	*yes*
C17 paper and pulp products	0.268*** (0.019)	0.228*** (0.039)	0.435*** (0.008)	371	56	0.00	*yes*
C18 printing and recorded media	0.116*** (0.026)	0.150*** (0.034)	0.306*** (0.069)	324	54	0.00	*yes*
C20 chemicals and chemical products	0.149*** (0.014)	0.110*** (0.032)	0.701*** (0.017)	493	83	0.23	*yes*
C21 pharmaceutical products	0.751*** (0.083)	0.175*** (0.026)	2.109*** (0.144)	207	31	0.00	*yes*
C22 rubber and plastics products	0.206*** (0.000)	0.129*** (0.000)	0.638*** (0.000)	1,308	209	0.00	*yes*
C23 other non-metallic mineral products	0.256*** (0.031)	0.031 (0.097)	0.693*** (0.099)	785	117	0.92	*yes*
C24 basic metals	0.216*** (0.017)	0.126*** (0.012)	0.633*** (0.007)	326	52	0.03	*yes*
C25 fabricated metal products	0.454*** (0.000)	−0.015*** (0.000)	0.492*** (0.000)	2,680	430	0.00	*yes*
C26 computer, electronic, optical products	0.485*** (0.074)	0.003 (0.019)	0.582*** (0.100)	748	107	0.68	*yes*
C27 electrical equipment	0.283*** (0.000)	0.060*** (0.000)	0.614*** (0.000)	665	99	0.00	*yes*
C28 machinery	0.288*** (0.003)	0.022** (0.011)	0.628*** (0.006)	1,377	215	0.00	*yes*
C29 motor vehicles, trailers, semi-trailers	0.351*** (0.009)	0.125*** (0.012)	0.561*** (0.002)	875	130	0.00	*yes*
C30 other transport equipment	0.277*** (0.082)	0.047 (0.034)	0.693*** (0.204)	127	19	1.00	*no*
C31 furniture	0.286 (0.448)	0.052 (0.082)	0.623 (0.975)	316	50	1.00	*yes*
C32 other manufacturing	0.396*** (0.030)	0.115** (0.055)	0.519*** (0.027)	354	63	0.72	*yes*
C33 repair, installation	0.511 (0.426)	−0.097 (0.167)	0.550 (0.514)	279	50	1.00	*yes*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table I.3: Results of production function estimation for Hungary

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.164*** (0.008)	0.033 (0.034)	0.778*** (0.015)	2,058	385	0.06	*yes*
C11 beverages	0.197*** (0.014)	0.054* (0.030)	0.818*** (0.029)	445	74	0.11	*yes*
C13 textiles	0.288*** (0.005)	0.090*** (0.023)	0.540*** (0.008)	435	77	0.00	*yes*
C14 wearing apparel	0.396*** (0.063)	0.038 (0.033)	0.474*** (0.042)	762	140	0.28	*yes*
C15 leather	0.463*** (0.016)	0.030 (0.033)	0.485*** (0.014)	308	53	0.54	*yes*
C16 wood products	0.115*** (0.011)	0.030 (0.037)	0.673*** (0.013)	1,473	262	0.00	*yes*
C17 paper and pulp products	0.026 (0.083)	0.151*** (0.043)	0.727*** (0.026)	345	55	0.05	*no*
C18 printing and recorded media	0.139*** (0.040)	0.157** (0.066)	0.580*** (0.013)	473	79	0.00	*yes*
C20 chemicals and chemical products	0.104 (0.083)	0.186*** (0.042)	0.637 (0.414)	384	70	0.89	*no*
C21 pharmaceutical products	*NA* *NA*	*NA* *NA*	*NA* *NA*	86	13	*NA*	*no*
C22 rubber and plastics products	0.164*** (0.009)	0.035 (0.022)	0.812*** (0.009)	1,754	287	0.56	*yes*
C23 other non-metallic mineral products	0.093*** (0.014)	0.038 (0.045)	0.787*** (0.018)	986	166	0.03	*yes*
C24 basic metals	0.131*** (0.019)	0.034 (0.059)	0.761*** (0.042)	377	59	0.02	*no*
C25 fabricated metal products	0.200*** (0.008)	−0.005 (0.013)	0.570*** (0.015)	4,875	863	0.00	*yes*
C26 computer, electronic, optical products	0.158*** (0.034)	−0.055 (0.041)	0.768*** (0.061)	571	103	0.01	*yes*
C27 electrical equipment	0.337*** (0.007)	0.047*** (0.013)	0.548*** (0.003)	1,056	168	0.00	*yes*
C28 machinery	0.221*** (0.009)	0.076*** (0.018)	0.634*** (0.014)	1,770	292	0.00	*yes*
C29 motor vehicles, trailers, semi-trailers	0.340*** (0.026)	0.130*** (0.047)	0.661*** (0.020)	757	126	0.00	*no*
C30 other transport equipment	0.276*** (0.118)	0.014 (0.051)	0.674*** (0.023)	142	23	0.62	*yes*
C31 furniture	0.162 (0.328)	0.032 (0.298)	0.681 (1.617)	781	132	1.00	*yes*
C32 other manufacturing	0.257*** (0.013)	0.025 (0.032)	0.632*** (0.008)	383	65	0.00	*no*
C33 repair, installation	0.372*** (0.022)	0.007 (0.030)	0.526*** (0.014)	1,238	202	0.01	*yes*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table I.4: Results of production function estimation for Slovakia

Industry	Labour (1)	Capital (2)	Material (3)	Number Observations (4)	Number Firms (5)	p-Value CRS (6)	Attrition (7)
C10 food products	0.275*** (0.000)	0.015*** (0.000)	0.671*** (0.000)	915	143	0.00	*yes*
C11 beverages	0.283*** (0.017)	0.088** (0.036)	0.693*** (0.027)	104	16	0.00	*no*
C13 textiles	0.215*** (0.000)	0.228*** (0.000)	0.447*** (0.000)	294	42	0.00	*no*
C14 wearing apparel	0.520* (0.307)	0.033 (0.023)	0.509* (0.299)	183	28	0.92	*no*
C15 leather	0.372*** (0.005)	0.053*** (0.010)	0.443*** (0.013)	115	15	0.00	*yes*
C16 wood products	0.359* (0.213)	0.002* (0.001)	0.525* (0.311)	983	152	0.82	*yes*
C17 paper and pulp products	0.150*** (0.014)	0.077*** (0.026)	0.741*** (0.009)	267	38	0.04	*yes*
C18 printing and recorded media	0.307*** (0.009)	0.092** (0.042)	0.406*** (0.022)	441	67	0.00	*no*
C20 chemicals and chemical products	0.267*** (0.009)	0.043** (0.019)	0.708*** (0.013)	443	60	0.11	*no*
C21 pharmaceutical products	*NA* *NA*	*NA* *NA*	*NA* *NA*	44	6	*NA*	*no*
C22 rubber and plastics products	0.379*** (0.002)	0.067*** (0.008)	0.474*** (0.004)	1,410	213	0.00	*yes*
C23 other non-metallic mineral products	0.300** (0.131)	0.176** (0.086)	0.466** (0.216)	525	76	0.89	*yes*
C24 basic metals	0.300*** (0.095)	0.063 (0.070)	0.588*** (0.188)	320	44	0.84	*yes*
C25 fabricated metal products	0.487*** (0.000)	0.012*** (0.000)	0.382*** (0.000)	3,406	522	0.00	*yes*
C26 computer, electronic, optical products	0.273*** (0.005)	0.094*** (0.017)	0.495*** (0.002)	572	78	0.00	*yes*
C27 electrical equipment	0.348 (0.242)	0.081 (0.057)	0.500 (0.348)	641	92	0.92	*no*
C28 machinery	0.316*** (0.002)	0.030*** (0.006)	0.585*** (0.003)	1,463	202	0.00	*yes*
C29 motor vehicles, trailers, semi-trailers	0.324*** (0.001)	0.033*** (0.003)	0.596*** (0.007)	343	51	0.00	*no*
C30 other transport equipment	*NA* *NA*	*NA* *NA*	*NA* *NA*	85	14	*NA*	*no*
C31 furniture	0.301*** (0.000)	0.006*** (0.000)	0.535*** (0.000)	621	91	0.00	*yes*
C32 other manufacturing	0.420** (0.185)	0.019 (0.011)	0.458** (0.204)	291	41	0.79	*no*
C33 repair, installation	0.583*** (0.009)	0.019 (0.032)	0.296*** (0.009)	561	104	0.00	*yes*
Note:	All elasticities are cluster bootstrapped at the firm-level. Firms with negative or zero output and input amounts are automatically dropped by using logged variables. *p<0.1; **p<0.05; ***p<0.01						

Table I.5: Results of production function estimation for Slovenia

I Estimates of the first stage

J Estimates of country-industry-level measures of concentration

The first country-industry-level of measure used is the HHI, being the sum of squared market shares calculated from the firm-level real operating revenues, $OPRE$. It varies between zero (perfect competition) and one (monopoly). In comparison, the CR4 is the sum of the market shares of the four largest firms. Last, Theil's L, S and T indexes, also being calculated from the firm-level real operating revenues, vary between zero and infinity. The larger the value, the more concentrated is the market. Due to their formulas, their coefficients cannot be interpreted in a meaningful way (Atayde *et al.* (2021), Opoku *et al.* (2020), Lu & Yu (2015), Inui *et al.* (2012)). In equation (J.1), showing each measure's formula, N denotes the number of firms by country, three-digit NACE industry and year and $\overline{OPRE}$ the average operating revenue varying at the same level.

$$
\begin{aligned}
HHI_{c,\,s,\,t} \;&=\; \sum_{i=1}^{N_{c,\,s,\,t}} \frac{OPRE_{i,\,t}}{\sum_{i=1}^{N_{c,\,s,\,t}} OPRE_{i,\,t}} \\
CR4_{c,\,s,\,t} \;&=\; \sum_{i=1}^{4} \max_{\{4\}} \frac{OPRE_{i,\,t}}{\sum_{i=1}^{N_{c,\,s,\,t}} OPRE_{i,\,t}} \\
Theil's\, L_{c,\,s,\,t} \;&=\; \frac{1}{N_{c,\,s,\,t}} \cdot \sum_{i=1}^{N_{c,\,s,\,t}} log\left(\frac{\overline{OPRE}_{c,\,s,\,t}}{OPRE_{i,\,t}}\right) \\
Theil's\, S_{c,\,s,\,t} \;&=\; \sum_{i=1}^{N_{c,\,s,\,t}} \left\{ \frac{OPRE_{i,\,t}}{N_{c,\,s,\,t} \cdot \overline{OPRE}_{c,\,s,\,t}} \cdot log\left(\frac{N_{c,\,s,\,t} \cdot \overline{OPRE}_{c,\,s,\,t}}{OPRE_{i,\,t}}\right)\right\} \\
Theil's\, T_{c,\,s,\,t} \;&=\; \frac{1}{N_{c,\,s,\,t}} \cdot \sum_{i=1}^{N_{c,\,s,\,t}} \frac{OPRE_{i,\,t}}{\overline{OPRE}_{c,\,s,\,t}} \cdot log\left(\frac{OPRE_{i,\,t}}{\overline{OPRE}_{c,\,s,\,t}}\right)
\end{aligned}
\tag{J.1}
$$

	Dependent Variable: $\Delta log(TFP)$				
	HHI	CR4	Theil's L	Theil's S	Theil's T
	(1)	(2)	(3)	(4)	(5)
HHI_t	0.135				
	(0.116)				
Squared HHI_t	−0.021				
	(0.165)				
$CR4_t$		0.142			
		(0.091)			
Squared $CR4_t$		−0.079			
		(0.090)			
Theil's L_t			0.359**		
			(0.162)		
Squared Theil's L_t			−0.081		
			(0.050)		
Theil's S_t				0.473***	
				(0.166)	
Squared Theil's S_t				−0.148**	
				(0.065)	
Theil's T_t					0.865**
					(0.342)
Squared Theil's T_t					−0.421**
					(0.206)
Log(real total $assets_{t-1}$)	0.020***	0.020***	0.020***	0.020***	0.020***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(average real $wage_{t-1}$)	−0.204***	−0.204***	−0.204***	−0.204***	−0.204***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
R-squared	0.119	0.119	0.062	0.062	0.042
Observations	83964	83964	82879	82879	82879
Units	15902	15902	14817	14817	14817
Underidentification					
Kleibergen-Paap rk LM statistic			38.181	38.554	10.292
p-value			0.000	0.000	0.001
Weak identification					
Cragg-Donald Wald F statistic			441.273	396.543	80.936
Kleibergen-Paap rk Wald F statistic			25.464	46.818	6.710
Stock-Yogo weak ID test critical values					
10% maximal IV size			7.03	7.03	7.03
15% maximal IV size			4.58	4.58	4.58
20% maximal IV size			3.95	3.95	3.95
25% maximal IV size			3.63	3.63	3.63
Endogeneity					
Endogeneity test			8.555	10.352	11.959
p-value			0.014	0.006	0.003
Firm-FE	*yes*	*yes*	*yes*	*yes*	*yes*
Country-year dummies	*yes*	*yes*	*yes*	*yes*	*yes*
Industry-year dummies	*yes*	*yes*	*yes*	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the firm-level.				
					*p<0.1; **p<0.05; ***p<0.01

Table J.1: Results of examination of first proposition using country-industry-level measures of market concentration

K Estimates for high-tech and low-tech industries

	Dependent Variable: $\Delta log(TFP)$			
	High-tech Lerner index (ROS)	Low-tech Lerner index (ROS)	High-tech Lerner index (Productivity)	Low-tech Lerner index (Productivity)
	(1)	(2)	(3)	(4)
Lerner index$_t$	1.979	1.392*	−0.419	1.437***
	(1.432)	(0.743)	(0.742)	(0.406)
Squared lerner index$_t$	−8.730***	−6.711***	−1.460	−3.546***
	(2.760)	(1.370)	(1.059)	(0.661)
Log(real total assets$_{t-1}$)	0.030***	0.015**	0.036***	0.021***
	(0.010)	(0.007)	(0.010)	(0.007)
Log(average real wage$_{t-1}$)	−0.239***	−0.213***	−0.288***	−0.186***
	(0.025)	(0.015)	(0.036)	(0.016)
R-squared	−4.019	−3.028	−0.324	−0.548
Observations	21643	54133	12109	30389
Units	3918	10033	2762	7005
Underidentification				
Kleibergen-Paap rk LM statistic	49.339	129.882	133.699	293.932
p-value	0.000	0.000	0.000	0.000
Weak identification				
Cragg-Donald Wald F statistic	201.742	658.922	138.277	479.573
Kleibergen-Paap rk Wald F statistic	21.061	62.856	69.945	171.111
Stock-Yogo weak ID test critical values				
10% maximal IV size	7.03	7.03	7.03	7.03
15% maximal IV size	4.58	4.58	4.58	4.58
20% maximal IV size	3.95	3.95	3.95	3.95
25% maximal IV size	3.63	3.63	3.63	3.63
Endogeneity				
Endogeneity test	323.232	676.086	21.284	61.809
p-value	0.000	0.000	0.000	0.000
Firm-FE	*yes*	*yes*	*yes*	*yes*
Country-year dummies	*yes*	*yes*	*yes*	*yes*
Industry-year dummies	*yes*	*yes*	*yes*	*yes*
Note:	All standard errors, in parenthesis, are clustered at the firm-level.			
				*p<0.1; **p<0.05; ***p<0.01

Table K.1: Results of examination of first proposition for high-tech and low-tech industries

Are Governments bad Entrepreneurs? On Productivity and Public Ownership in Central European post-communist Countries

Particular acknowledgements: I would like to thank Marina Di Giacomo (University of Turin) for her support.

Abstract: Although Central European post-communist countries have considerably liberalized energy sectors, privatisations were poorly implemented establishing legal monopolies and retaining governments' pervasive influence. This study examines the effects of public ownership on productivity and market power, using a dataset on Central European firms, operating in industries of general interest, from 2009 to 2017. This study contributes to the literature by also establishing a link between public ownership and market power. The overall results highlight that public ownership is associated with significant productivity losses, which increase over quantiles, and lower market power.

JEL: L25, L97, L32

Keywords: Productivity, Public Utilities, State Owned Enterprises

1 Introduction

In previous decades, EU member states liberalized energy sectors (e.g. unbundling, elimination of entry barriers etc.) and privatized public companies to establish competition between energy suppliers [1]. Nevertheless, many segments including generation are still highly concentrated today. [2] In comparison to energy generation, transmission and distribution are heavily regulated, since these segments suffer from natural monopolies due to high sunk costs of constructing grids (Ajayi *et al.* (2017), Armstrong & Sappington (2007)). In comparison, the steam and air conditioning industry is weakly regulated (e.g. there is no single market, neither national ones nor an EU-wide one), decentralized and fragmented (products cannot be transported economically on long distances and, therefore, are consumed locally) (European Commission (2016)).

A long-held, and frequently examined proposition in Economics is that public firms produce less efficiently and profitably than private firms. As highlighted by Sappington & Stiglitz (1987), federal governments have the differential ability to intervene in production processes of private and public firms. In the case of public firms, federal governments can influence production processes more easily. Many economists argue that public ownership reduces firm performance, as governments cannot generally commit and, thus, appropriate the surpluses generated from investment. Consequently, private firms face stronger incentives to cut costs and raise efficiency ('hold-up problem') (Shleifer (1998), Hart *et al.* (1997)). Besides, state-owned enterprises are also often consumed by other interest groups such employees and managers. Next to national governments, these interest groups treat the firm as public property damaging firm value ('tragedy of the commons') (Iwasaki *et al.* (2022)). Next, state owners try to achieve political goals (e.g. keeping up employment, protecting specific industries, providing public services) through public companies. In other words, they prioritise political goals over profit maximisation implying efficiency losses (Iwasaki *et al.* (2022), Mühlenkamp (2015)). Furthermore, the state-owned firms benefit from softer budget constraints, i.e.: governments are likely to bail relevant companies out in case of bankruptcy, reducing incentives to produce efficiently and profitably. Moreover, publicly owned companies suffer from bureaucracy and information asymmetries between the top management and governmental owners implying a lack of transparency in decision-making processes and higher monitoring costs. Both issues weaken firm performance of state-owned enterprises (Iwasaki *et al.* (2022)). The empirical literature (e.g. Iwasaki *et al.* (2022), Castelnovo *et al.* (2019), Bogart & Chaudhary (2015), Del Bo (2013), Brown *et al.* (2006), Djankov & Murrell (2002), Megginson & Netter (2002)) confirms that private firms are more productive than public firms, implying that state ownership has efficiency costs. Castelnovo *et al.* (2019) investigate the effects of public ownership and institutional environment quality on telecommunication companies' productivity and find a significantly negative impact of public ownership, which is, however, mitigated by high institutional quality. Bogart & Chaudhary (2015) study the effect of state takeovers on the productivity of Indian railway companies in the 19th century,

[1] For instance, see `https://stats.oecd.org/Index.aspx?DataSetCode=ETCR` or `https://stats.oecd.org/Index.aspx?DataSetCode=SECTREG2018`

[2] This finding can be observed from the market shares of the largest electricity generators, downloadable from Eurostat (`https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=nrg_ind_331a&lang=en`).

and conclude that, instead of reducing productivity, public ownership maintained technical efficiency. Next, Del Bo (2013) estimates the productivity differentials between European private and public, domestic and foreign electricity generators, and finds that foreign firms are more productive than domestic companies. Particularly, foreign public firms produce more efficiently than their private pendants, while conclusions whether domestic public firms are more productive than domestic private firms vary across quantiles and functional forms. Moreover, Frydman *et al.* (1999) observe that privatization improves revenue performance of formerly public firms in Eastern European countries, but does not affect cost efficiency. In comparison to selling the firm to inside owners (managers, workers, state in a privatized firm), only selling it to outside owners affects efficiency. Similarly, Brown *et al.* (2006), Warzynski (2003) and Jones & Mygind (2002) also find significantly positive effects of privatisations on the productivity of Eastern European companies. Conversely, Lazzarini & Musacchio (2018) find that public firms only underperform private companies in economic downturns. This study combines the approaches of many other studies and, therefore, adds to the literature in several aspects. First, to the best of my knowledge, this the first study establishing a link between public ownership and market power. This link is of particular interest, as public ownership is usually justified by arguing that public monopolists also pursue goals other than profit maximization and reaping consumer rent. Second, although I follow the literature and employ a binary variable for publicly owned firms, I also use the shares owned by public authorities, being a novelty with respect to the existing literature (Borghi *et al.* (2016), Castelnovo *et al.* (2019)). Third, this one of the few studies (e.g. Del Bo (2013)) investigating the effects of public ownership on different quantiles of the productivity distribution. Fourth, many studies (e.g. Castelnovo *et al.* (2019), Lazzarini & Musacchio (2018), Frydman *et al.* (1999)) investigating the effects of privatization only consider large listed firms, while I also involve smaller firms with many of them being municipal utilities.

Motivated by this aspect, the following article explores the effects of firm-level public ownership on productivity and market power. Therefore, micro-data on electricity (D351) and steam and air condition firms (D352) from Czech Republic, Hungary and Slovakia during 2009-2017 are employed. The core business of relevant firms primarily covers energy generation (e.g. electricity, steam and air conditioning) and their distribution. The energy industry is of special interest for two reasons. First, although governments have eliminated market barriers by vertically disintegrating generation and grids, markets are still concentrated. Second, many companies in network industries are publicly owned to overcome problems resulting from to weak competition. Post-communist countries are particularly interesting due to their history. Analysed countries transitioned from planned to market economies after the collapse of the Soviet Union experiencing major institutional changes and liberalizations, although the government's influence in these countries is still pervasive. Especially post-communist countries are characterized by strong entry barriers aggravating the transition to well-functioning market economies. Furthermore, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies strengthening market barriers (Buccirossi & Ciari (2018)). Furthermore, the three countries do not only belong to Continental Central-East region, but are also members of the Visegrad group, the longest and most developed and important regional cooperation within Central Europe. National network industries are highly interlinked with each other, but also with their Western neighbours (e.g. Austria, Germany) (CEEP (2018)). Given theory and empirical findings, I hypothesize that higher market power decreases technical efficiency in these industries.

I apply a two-staged framework. In the first stage, I estimate translog production functions applying the algorithm by Ackerberg *et al.* (2015) to obtain technical efficiency. In the second-stage, I regress productivity and Lerner indexes on public ownership variables applying quantile regression.

Generally, the results show that public ownership is associated with significant productivity losses which are larger at higher deciles of the productivity distribution. In other words, public firms operate significantly less efficiently than their private pendants, suggesting to continue privatization or to design policies explicitly focusing on raising productive efficiency of publicly owned companies. Moreover, a higher degree of public ownership is associated with lower Lerner indexes (profitability) as well. Furthermore, average real wages raise productivity, as more human capital allows firms to produce more efficiently. Last, larger firms operate less efficiently implying that firms suffer from incomplete structural reforms and misallocations during the Soviet era.

The paper proceeds as follows. *Section 2* briefly introduces the empirical framework and data, used to examine the impacts of public ownership on productivity and market power, while *Section 3* provides the results of the estimations of the production function, discusses the estimated effects and shows some robustness checks. Last, *Section 4* sums up and draws conclusions.

2 Empirical strategy and data

2.1 First stage: estimation of the production function

I follow the literature (e.g. Commins *et al.* (2011), Combes *et al.* (2012), Crinò & Epifani (2012), De Loecker & Warzynski (2012), Higón & Antolín (2012), Holl (2012), Newman *et al.* (2015)) and consider a two-input value added-based second-order translog production function, as described in equation (1). y denotes logged value added (dependent variable), k logged capital (state variable) and l logged labour (free variable). This particular specification assumes that material evolves proportionally with output. In other words, a fixed proportion of material is used to generate one unit of output (Leontief) (Ackerberg *et al.* (2015), De Loecker & Warzynski (2012)). ζ is the sum of unobserved productivity ω and the measurement error of the productivity shock ψ. The indices i and t represent firms and years. Although Cobb-Douglas production functions are probably the most popular function type, I choose a translog specification, because it is more flexible, though data demanding (Syverson (2011)). The polynomial involves all logged inputs, their squares, and all their interaction terms (De Loecker & Warzynski (2012)).

$$
\begin{aligned}
y_{i,t} = & \beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \\
& \beta_{kk} \cdot k_{i,t}^2 + \beta_{ll} \cdot l_{i,t}^2 + \\
& \beta_{kl} \cdot k_{i,t} \cdot l_{i,t} + \underbrace{\omega_{i,t} + \psi_{i,t}}_{\zeta_{i,t}}
\end{aligned}
\tag{1}
$$

For any given firm i, in any given year t, output elasticities of the variables are calculated by taking the first-order derivatives.

$$
\begin{aligned}
\frac{\partial y_{i,t}}{\partial k_{i,t}} &= \beta_k + 2 \cdot \beta_{kk} \cdot k_{i,t} + \beta_{kl} \cdot l_{i,t} \\
\frac{\partial y_{i,t}}{\partial l_{i,t}} &= \beta_l + 2 \cdot \beta_{ll} \cdot l_{i,t} + \beta_{kl} \cdot k_{i,t}
\end{aligned}
\tag{2}
$$

I estimate the production function applying the method by Ackerberg *et al.* (2015), using l as free variable, k as state variable and logged material m as proxy variable (Richter & Schiersch (2017), Collard-Wexler & De Loecker (2015), Lu & Yu (2015), De Loecker & Warzynski (2012), Higón & Antolín (2012)). A brief explanation of the algorithm is provided in appendix L. To allow for heterogenous input elasticities β across country levels, I follow the literature (e.g. Fons-Rosen *et al.* (2021), Gemmell *et al.* (2018), Levine & Warusawitharana (2021), Olper *et al.* (2016)) and estimate equation (1) for each country pooling observations across two-digit NACE industries. After estimating the production function, derived input elasticities are used to construct logged total factor productivity $log(TFP)$ for each sampled firm i and year t, as shown in equation (3). As productivity is the residual, it quantifies the changes in output while keeping inputs constant. Owing to the logged dependent variable, productivity is also logged (Javorcik (2004), Olley & Pakes (1996)).

$$
\begin{aligned}
log(TFP_{i,t}) = & y_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} \\
& - \beta_{kk} \cdot k_{i,t}^2 - \beta_{ll} \cdot l_{i,t}^2 \\
& - \beta_{kl} \cdot k_{i,t} \cdot l_{i,t}
\end{aligned}
\tag{3}
$$

2.1.1 Data

As product-level output and input quantities are usually not available, while monetary outputs and inputs are only available as firm-level aggregates, I follow the literature and estimate the production function based on producers' real total monetary operating revenues, capital and material expenditures.

Firm-level data is downloaded from the Orbis database. Orbis, published by Bureau van Dijk, provides accounting data, legal form, industry activity codes, and incorporation date for a large set of private and public firms worldwide. I include medium sized, large and very large [3]; active and inactive companies from sector D ('electricity, steam and air conditioning', e.g.: electricity generation, transmission etc.), incorporated in the Czech Republic, Hungary and Slovakia. [4] The final sample is a nine-year unbalanced panel dataset, from 2009 to 2017. It contains 809 firms with 5,008 observations. [5] [6]

Output is defined as real value added, the difference between real operating revenues and real material expenditures [7] (Combes *et al.* (2012), Crinò & Epifani (2012), Holl (2012), Newman *et al.* (2015)). [8] Operating revenues, covering net sales, other operating revenues and stock variations excluding VAT (Bureau van Dijk (2007)), are deflated by annual producer price indices, obtained from the Eurostat database [9], varying across countries, two-digit NACE industries and years. Next, real material expenditures, approximating material, are computed by deflating material costs, defined as the sum of expenditures on raw materials and intermediate goods, by an uniform intermediate good price index, sourced from the Orbis database [10], varying across countries and years. Next, real tangible fixed assets (e.g.: machinery), approximating capital, are calculated by deflating tangible fixed assets by an uniform investment good price index, downloaded from the same database [10], varying across countries and years. Last, labour is a physical measure of the total number of employees included in the company's payroll. (Castelnovo *et al.* (2019), Richter & Schiersch (2017), Du *et al.* (2014), Nishitani *et al.* (2014), Baghdasaryan & la Cour (2013), Del Bo (2013), Crinò & Epifani (2012), Higón & Antolín (2012), Javorcik (2004)).

2.2 Second stage: estimation of productivity and Lerner indexes

To examine the effects of public ownership on a set of dependent variables W across different quantiles, I follow Del Bo (2013) and employ quantile estimation, regressing the dependent variable on public ownership $PUBLIC$, control variables X and Z, and nested three-digit NACE industry-year dummies, as shown in equation (4). The indices i, t, c and s denote firms, years,

[3] Orbis considers firms to be 'medium sized', when operating revenues $\geq$ 1 mio EUR or total assets $\geq$ 2 mio EUR or employees $\geq$ 15. Orbis defines firms to be 'large', when operating revenues $\geq$ 10 mio EUR or total assets $\geq$ 20 mio EUR or employees $\geq$ 150. Firms are 'very large', when operating revenues $\geq$ 100 mio EUR or total assets $\geq$ 200 mio EUR or employees $\geq$ 1,000 or the company is listed (Bureau van Dijk (2007)).

[4] I exclude the gas sector (D 352) given the small number of observations.

[5] As data on Slovakia 2017 were only barely available in Orbis, I exclude the few available observations.

[6] Observations with implausible output and input values (e.g. negative values) or missing values are dropped. Firms with either unknown or unavailable activity status are eliminated.

[7] Observations with negative value added, though included in the dataset, are not used to perform regressions.

[8] I use double deflated not single deflated value added. Stoneman & Francis (1994) provide a discussion of the pros and cons of each method.

[9] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=sts_inpp_a&lang=de`

[10] `https://stats.oecd.org/Index.aspx?DataSetCode=MEI_PRICES_PPI`

countries and three-digit NACE industries. ρ is the intercept.

$$\begin{aligned} W_{i,t} = &\rho + \delta \cdot PUBLIC_{i,t} + \beta \cdot X_{i,t-1} + \alpha \cdot age_{i,t} + \kappa \cdot Z_i \\ &+ \sum_{c=1}^{C} \sum_{s=1}^{S} \sum_{t=2010}^{2017} \gamma_{c,s,t} \cdot D_c \cdot D_s \cdot D_t + \epsilon_{i,t} \end{aligned} \tag{4}$$

The first dependent variable is logged productivity $log(TFP)$ obtained in the first stage. The second dependent variables is the Lerner index to establish a link between public ownership and market power. Lerner indexes are measured by the return on sales, being the share of variable profits in revenues (Bayeh *et al.* (2021), Atayde *et al.* (2021), Daveri *et al.* (2016), Inui *et al.* (2012), Aghion *et al.* (2008)). As the dataset does not contain data on profits, I define profits as the difference between real operating revenues and the sum of real material costs and wage expenditures following Aghion *et al.* (2008) which simplifies to one minus the shares of real wages and real material costs in real operating revenues. Although this measure does not include capital costs (e.g. interest costs), as they are mostly missing, it is only a minor issue, since only standard errors will increase. Only observations with $LI \in [0, 1]$ are included, as Lerner indexes lying outside the interval imply either that prices do not cover marginal costs, some products of multi-product firms are complements, or that marginal costs are negative (Tirole (1994)). In other words, observations with Lerner indexes lying outside the interval do not provide information on the degree of market power and, therefore, would bias results and turn them meaningless.

Like the literature (e.g. Castelnovo *et al.* (2019), Del Bo (2013)), I replace unobserved firm-level heterogeneity with time-invariant variables given the strong persistency of ownership structures, i.e.: firm-level fixed effects would cut variation in the variable of interest implying that its coefficient will be regressed from the few firms experiencing changes in public ownership. I follow Castelnovo *et al.* (2019), Lazzarini & Musacchio (2018), Scheffler *et al.* (2013) and Stiel *et al.* (2017) and introduce contemporaneous public ownership as exogenous variables. First, only few privatisations have been implemented. Second, shareholdings are highly stable over time, since adjustments to the capital structure cannot be introduced easily in the short-run.

To estimate the effects of public ownership, I employ a large set of measures, as indicated by $PUBLIC$. I only consider domestic public ownership [11] and do not take account of foreign public owners. $PUBLIC$ covers two different definitions of variables, constructed from the information on direct and total shareholdings owned by domestic public authorities in the firm's equity. Obvious keypunch errors in the type of shareholders are corrected.
In the first specification, I use the direct and total shareholdings owned by domestic public authorities. The 'direct share' solely includes direct property relationships [12], while 'total shares' also incorporate indirect property relationships. [13] Both variables only provide information on

[11] This is the government of the country, the company is incorporated in.
[12] E.g. the governments holds 30% in the firm's equity.
[13] E.g. the government holds 40% of the shares of firm A and holds 50% of the shares of firm B. On the other hand, firm B owns 30% of the shares of firm A. In total, the government holds 40% + 30% · 50% = 55% of the

the lowest stage of the shareholder pyramid and, therefore, should not be confused with ultimate ownership, i.e.: the owner at the top of the ownership pyramid. Generally, public authorities have not changed their shareholdings over time, as only few firms have experienced some privatization or nationalization. To consider multiple public shareholders, for both variables, the sums of the public shareholdings are computed. Generally, direct shares may be a better proxy of public ownership, because total shares suffer from missing values, and, therefore, the sum of the public direct shares might serve as a better proxy for the degree of public ownership. [14] Data on firm-level shareholdings owned by different types of shareholders (public authorities, companies, funds etc.) is obtained from Orbis.

I only employ observations for which sufficient information on the shareholder structure is available. Therefore, I compute the sum of all direct shareholdings across all shareholder types for every firm and year. If a shareholder sells his shares to another one, the sum exceeds 100 for a given firm and year. For the relevant observations, the buyer's share is kept constant, while the seller's share is reduced by the value sold, implying that the sums are always ≤ 100. In case of missing information, the sums, however, fall below 100. To only consider observations that do not suffer too much from missing information on the shareholder structure, I involve those for which $\geq 90\%$ of the direct shares are available. Dropping all the others for which sufficient information is not available, however, implies a loss of around the half of all observations. Using continuous variables does not only represent a novelty with respect to the previous literature investigating the performance differences between public and private firms, using dummy variables for public firms (Castelnovo *et al.* (2019), Borghi *et al.* (2016)), shares also capture the effect of the degree of public ownership in a more comprehensive way than binary variables do (Richter & Schiersch (2017), Cole *et al.* (2013)).

The second approach employs a simple definition of public firms, using binary variables. The first dummy equals one, if the sum of domestic public direct share exceeds zero, and is zero otherwise. Following Castelnovo *et al.* (2019), Lazzarini & Musacchio (2018), Scheffler *et al.* (2013) and Stiel *et al.* (2017), the second and third dummies are one, if the same variable $\geq 10\%$ and 50%. All the dummies are corrected for indirect ownership to classify firms that are only indirectly owned by public authorities [15] as public firms by replacing the values of the relevant observations with one. The correction, however, only works, if total shareholdings are available, allowing to consider indirect ownership to some limited degree.

Given the available literature, I expect public ownership to impact material intensity positively, as public companies produce less efficiently. For Lerner indexes I expect negative impacts, since public companies do not only operate less profitably, but also pursue goals other than profit maximization.

Vector X introduces time varying control variables, capturing other drivers of technological progress and reorganization within firms. They are lagged by one period to overcome reverse causality (Franco & Marin (2017), Inui *et al.* (2012)). [16]

---

shares of firm A.

[14] However, their correlation coefficient equals 0.9832, significantly deviating from zero.

[15] The direct share equals zero, but the total share exceeds zero.

[16] Relevant variables are usually influenced by contemporaneous productivity, i.e.: short-run rises in productivity will decrease imports and intensify competition in the same year, as they are newly determined every year.

First, I control for human capital and labour costs (Del Bo (2013), Commins *et al.* (2011)). I follow Del Bo (2013) and introduce the logged firm-level real wage per employee. Data on firm-level wage costs is sourced from Orbis, which are deflated by national consumer price indices (Arnold *et al.* (2011)), downloaded from Eurostat [17], and divided by firm-level employment. I expect the variable to raise productivity, as more human capital allows firms to produce more efficiently. On the other hand, the response of Lerner indexes is ambiguous. While productivity gains reduce marginal costs given prices, they allow companies to undercut competitors. Unlike these studies, I involve the variable lagged by one period, as human capital and wage costs can be easily adjusted within a given year.
Besides, following Castelnovo *et al.* (2019) and Del Bo (2013), I include the firm's logged real total assets to capture the effects of firm size. Unlike these studies, I introduce the variable lagged by one period, as contemporaneous investment will respond to technical efficiency and profitability. Given the literature, their effect is ambiguous, as empirical works find both, positive and negative, impacts (e.g. Castelnovo *et al.* (2019), De & Nagaraj (2014), Del Bo (2013), Ye *et al.* (2012), Diaz & Sanchez (2008), Yasuda (2005), Haltiwanger *et al.* (1999), Berger & Hannan (1998), Majumdar (1997)). On the one hand, larger companies benefit from economies of scale. On the other hand, constructing new plants is costly due to the high fixed costs. [18] Concerning Lerner indexes, larger firms plausibly benefit from more market power given the larger market shares.
Last, I include the firm's age, the difference between the given year and the year of foundation (Inui *et al.* (2012)). Data are obtained from Orbis and, in comparison to the former two variables, age is not lagged.

Furthermore, the specification involves time-invariant characteristics related to the firms' ownership structure Z obtained from Orbis. Since, capital structures and legal forms cannot be easily adjusted in the short run, they are introduced as exogenous variables. First, I introduce a binary variable for the standardized legal form, being one for public limited companies and zero for private limited firms. As public limited companies engage more in foreign business and exhibit more formal structures, I expect a positive effect (Del Bo (2013), Tomiura (2007)). The impact on profitability is ambiguous, because of the unclear effect of legal requirements. Second, I involve the number of shareholders. Its impact is ambiguous. On the one hand, firms with a larger number of shareholders benefit from diversified sources of finance. On the other hand, decisions in supervisory bodies might be more difficult, since more shareholders exert control rights raising pressure on the management. The analogous holds for Lerner indexes. Besides, I introduce nested country-3-digit NACE industry-year dummies $D_c \cdot D_s \cdot D_t$, capturing country-industry-specific differences between firms varying of years (e.g. business cycles, institutional quality, European policies etc.). [19]

[17] `https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=prc_hicp_aind&lang=de`
[18] The results do not change when employing other measures of firm size such as the logged number of employees or capital intensity.
[19] In total, regressions cover 52 nested dummies.

3 Results

In the first step of the analysis, I estimate the production function for each country. Summary statistics are displayed in the first block of *Table* 1. The second block shows the same for the regressions examining the effects of public ownership. Besides, the table also illustrates the high coverage of smaller firms (e.g. that only have few employees).

Variable	Unit	Mean (SD)	Min - Med - Max	IQR
First Stage				4,723 Observations
Real Operating Revenues	Tsd. Euro	41,920.1 (219,078.0)	0.3 < 2,693.8 < 5,769,749.0	8,139.0
Real Material Costs	Tsd. Euro	24,646.8 (156,944.9)	0.0 < 1,401.0 < 5,592,642.0	4,770.2
Real Value Added	Tsd. Euro	17,273.4 (98,264.5)	0.2 < 1,234.7 < 1,885,918.0	3,002.4
Real Tangible Fixed Assets	Tsd. Euro	35,233.6 (221,035.7)	0.0 < 3,313.7 < 4,928,768.0	8,582.0
Number of Employees	Integer	80.2 (219.3)	1.0 < 15.0 < 2,750.0	72.0
$log(TFP)$		17.0 (1.8)	6.5 < 17.4 < 23.4	2.5
Second Stage				2,463 Observations
$log(TFP)$		17.3 (1.7)	9.3 < 17.7 < 23.4	1.8
Lerner Index (Return on Sales)	Percent	0.4 (0.3)	0.0 < 0.3 < 1.0	0.5
Real Total Assets	Tsd. Euro	51,579.4 (288,754.0)	0.0 < 3,222.2 < 4,941,011.0	8,681.6
Average Real Wage	Tsd. Euro	21.9 (56.7)	0.0 < 15.9 < 1,865.7	13.4
Direct Shareholdings	Percentage Points	23.8 (41.5)	0.0 < 0.0 < 100.0	34.0
Total Shareholdings	Percentage Points	23.0 (42.1)	0.0 < 0.0 < 100.0	0.0
Dummy Direct Shareholdings > 0%	Binary	0.3 (0.4)	0.0 < 0.0 < 1.0	1.0
Dummy Direct Shareholdings > 10%	Binary	0.3 (0.4)	0.0 < 0.0 < 1.0	1.0
Dummy Direct Shareholdings > 50%	Binary	0.2 (0.4)	0.0 < 0.0 < 1.0	0.0
Age	Continuous	12.4 (6.9)	0.0 < 12.0 < 64.0	11.0
Dummy Public Limited Company	Binary	0.2 (0.4)	0.0 < 0.0 < 1.0	0.0
Number Shareholders	Continuous	1.5 (0.9)	0.0 < 1.0 < 8.0	1.0
Note:	'Mean' denotes the average, 'SD' the standard deviation, 'Min' the minimum value, 'Med' the median, 'Max' the maximum value, and 'IQR' the interquartile range. Some values (e.g. inputs, Lerner indexes) are shown to be zero given the rounding. Note that $log(TFP)$ and its level cannot be interpreted in a meaningful way.			

Table 1: Descriptive statistics

3.1 Results of the first stage

I perform the analysis as outlined in *Section* 2 and estimate the translog production function for each country. For each input, it follows a distribution of firm-level input elasticities of output that are obtained the way as shown in equation (2). *Table* 2 summarizes the expected values of the input elasticities. The columns display the elasticities of each input by countries, while the rows of the first block show the elasticities of each input. The rows of the second block provide the sum of elasticities, numbers of observations and firms.

Owing to the log-log representation, the expected partial effects are interpreted as elasticities, i.e.: in column (1), the capital elasticity of output equals 0.230, meaning that value added rises on average by 0.230%, when capital increases by 1%, keeping everything else constant. Results, though being heterogeneous across countries, are consistent with Higón & Antolín (2012) and Holl (2012) who also find capital elasticities between 0.10 and 0.30, and labour elasticities between 0.60 and 0.80. As can be concluded from the sum of the expected values of the elasticities, increasing returns to scale are observed in every country except the Czech Republic, supporting the hypothesis that energy industries, on average, are still benefiting from natural monopolies.

Figure 1 displays average Lerner indexes by three-digit NACE industries. Average return on sales-style Lerner in the electricity sectors are represented by the solid red line, while the ones for the steam and air conditioning industries are illustrated by blue dashed line. On average, Lerner

	Country		
	Czech Republic (1)	Hungary (2)	Slovakia (3)
Capital	0.230	0.272	0.412
Labour	0.683	0.919	0.698
Sum of Elasticities	0.913	1.191	1.110
Number of Observations	2,726	790	1,207
Number of Firms	474	117	198

Table 2: Expected input elasticities of output of the translog production function

indexes are higher in the electricity industry that is subject to incentive regulation spurring firms to produce more efficiently. In comparison, average Lerner indexes are smaller in the steam and air conditioning industry which is characterized by high sunk costs to construct and maintain local grids.

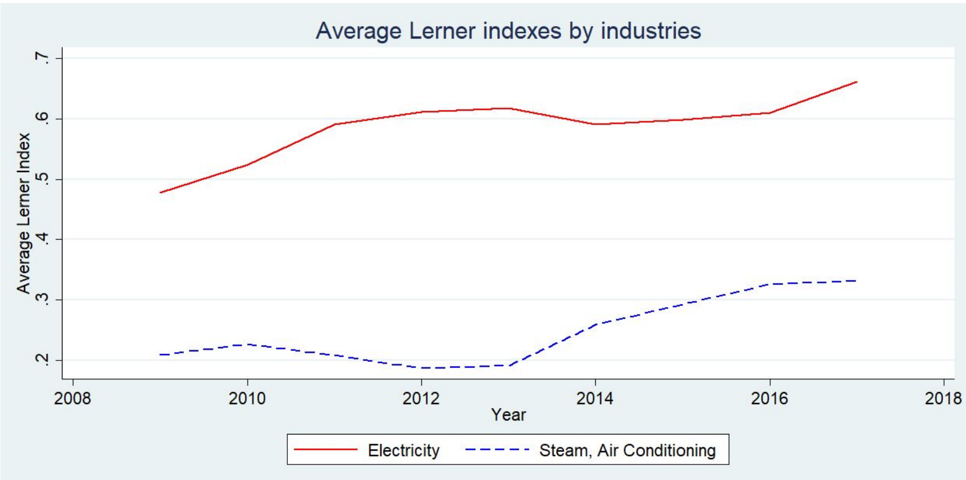

Figure 1: Average Lerner indexes by three-digit NACE industries

Figure 2 provides the average productivity growth rates by the same groups of industries. To obtain percentage points, underlying firm-level growth rates are calculated as the annual differences in $log(TFP)$ and multiplied by 100. On average, productivity grows more strongly in the electricity and gas industries with average growth rates usually between seven and 25 percentage points. In comparison, the steam and air conditioning industry recovered later from the financial crises.

3.2 Results of the second stage

Following sections describe the results of the quantile regressions for each dependent variable separately. First, the effects on productivity are discussed, followed by the impacts on the return on sales-style Lerner index.

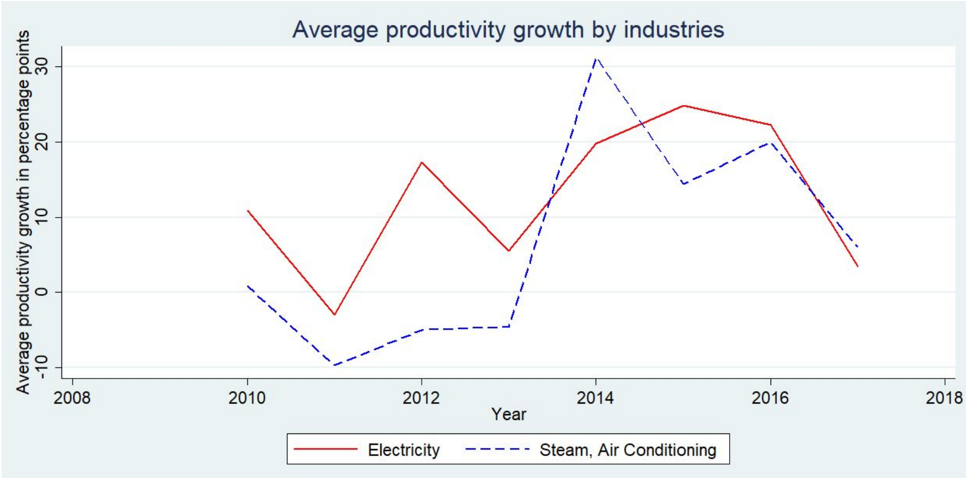

Figure 2: Average productivity growth by three-digit NACE industries

3.2.1 Impacts on productivity

Table 3 provides the results of the quantile regressions involving the first measure of public ownership, the sum of direct shareholdings owned by public authorities, as described in equation (4). The dependent variable is the firm-level logged productivity $log(TFP)$ in all the regressions. Standard errors are clustered at the firm-level to consider residual serial correlation, as suggested by the Parente-Santos Silva test shown at the bottom of the table.
The columns display the regressions for the median, the first and ninth deciles, and the first and third quartiles.
Compared to the first stage, the second stage employs less observations and firms, as I exclude observations for which sufficient information on the ownership structure is not available.

In every column, public ownership is associated with a significantly lower productivity. Owing to the log-level specification, the coefficients are interpreted as semi-elasticities, i.e.: if the direct share owned by domestic public authorities rises by 1 percentage point, productivity significantly declines by 0.4-0.6%. Their magnitudes resemble those by Del Bo (2013). As in Del Bo (2013), the productivity differentials between private and public domestic firms increase with the quantile, implying that more efficient firms suffer higher productivity losses when public ownership is raised. Plausibly, if productivity is low, public ownership, though still causing inefficiencies, does not decrease productivity that much, as productivity is already low. Conversely, for more efficient firms, public ownership is associated with higher efficiency losses, as productivity starts from a higher level. Coefficients are also in line with those of other studies, investigating the productivity differences between private and public firms of various public industries (e.g. Scheffler *et al.* (2013), Boitani *et al.* (2011)).

Firm size, as measured by logged real total assets, significantly decreases productivity in higher quantiles. Coefficients are interpreted as elasticities, i.e. if the variable rises by 1%, productivity significantly drops by 0.026-0.078%. In contrast to Del Bo (2013), larger firms produce significantly less efficiently than medium sized firms. The effect is more relevant for the right tail of the productivity distribution. In the literature, however, there is no consens whether smaller or larger companies produce more efficiently or grow faster then the others. My result, therefore, is in line with the literature concluding that larger firms produce less efficiently due to their complexity in organization and agency problems (De & Nagaraj (2014), Ye *et al.* (2012), Diaz & Sanchez (2008), Yasuda (2005), Haltiwanger *et al.* (1999), Berger & Hannan (1998), Majumdar (1997)). Often negative impacts are found in developing countries (De & Nagaraj (2014), Tybout (2000)). Hence, the results suggest that breaking up large state-owned companies (e.g. unbundling) spurred productivity in post-communist countries. In a historical sense, it supports the hypothesis that communists have not allocated resources efficiently by excessively promoting large companies that still benefit from governmental support (Buccirossi & Ciari (2018)). De Rosa *et al.* (2015), also observing negative effects of firm size on Eastern European companies' productivity, argue that the result may be a sign of incomplete restructuring (e.g.: regulations primarily targeted larger firms decreasing their efficiency). Besides, building up capacities is costly and consumes many years, as new plants have to be constructed (semi-fixed costs), dominating the productivity gains from economies of scale. [20] All these issues affect more efficient firms more strongly.

As expected, average real wages raise productivity, as more human capital allows firms to produce more efficiently. A rise by 1% significantly spurs technical efficiency increases by 0.060-0.349%. Effects increase with quantiles, suggesting that effects are more relevant at the right tail of the productivity distribution. The coefficients' magnitudes resemble the ones by Del Bo (2013) lying between 0.2 and 0.4.

Older firms, however, produce significantly less efficiently. Impacts are stronger at higher deciles. Its coefficient is interpreted as semi-elasticity. An increase by one year drops efficiency by 0.7-2.3%. The reason might be that older firms may be more bureaucratic with rigid organizational structures that hurt more productive firms more. These firms might also engage more in rent-seeking. As compared with private limited companies, public limited companies produce more efficiently in higher quantiles, but less productively in the lowest quantile. Relevant firms tend to operate internationally and underlying regulations will only benefit more efficient firms given their strictness. Productivity differentials range between -30.9 and +22.3%. The number of shareholders plausibly only affects less efficient firms which benefit more from a more diversified shareholder structure, as they have not completely exploited the efficiency potential. As more productive firms are already close to their efficiency potential, funds from an additional shareholder do not contribute to technical efficiency anymore. In the lowest quantile, an additional shareholder raises technical efficiency by 11.5%.

The same conclusions are drawn when employing the publicly owned total shareholdings, as described in *Table* 4.

In the regressions shown in *Tables* 5, 6, and 7, I involve binary variables. They equal one, if the shareholdings owned by domestic public authorities are $> 0\%$, $\geq 10\%$, and $\geq 50\%$ re-

[20] As shown in *Table* 2, only mild increasing returns to scale are observed.

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Direct Shareholding	−0.004∗∗∗	−0.005∗∗∗	−0.005∗∗∗	−0.006∗∗∗	−0.006∗∗∗
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged log(real total assets)	0.015	−0.026	−0.036	−0.051∗∗	−0.078∗∗
	(0.029)	(0.021)	(0.025)	(0.025)	(0.035)
Lagged log(average real wage)	0.060	0.164∗∗	0.217∗∗∗	0.219∗∗∗	0.349∗∗∗
	(0.110)	(0.082)	(0.054)	(0.049)	(0.070)
Age	−0.007	−0.014∗	−0.013∗∗∗	−0.015∗∗∗	−0.023∗∗∗
	(0.007)	(0.007)	(0.005)	(0.004)	(0.007)
Dummy for public limited company	−0.309∗	−0.008	0.159	0.244∗∗∗	0.223∗∗
	(0.168)	(0.125)	(0.103)	(0.093)	(0.109)
Number Shareholders	0.115∗∗∗	0.067∗∗	0.003	−0.005	0.017
	(0.033)	(0.027)	(0.026)	(0.045)	(0.038)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.639	0.703	0.717	0.711	0.653
Observations	1932	1932	1932	1932	1932
Units	504	504	504	504	504
Objective Function	0.145	0.248	0.299	0.242	0.141
Parente-Santos Silva test	20.511	25.000	28.726	29.056	29.709
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 3: Regressions of logged productivity introducing direct shareholdings

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Total Shareholding	$-0.004***$	$-0.005***$	$-0.005***$	$-0.006***$	$-0.006***$
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged log(real total assets)	0.019	-0.024	-0.030	$-0.052**$	$-0.079**$
	(0.027)	(0.022)	(0.026)	(0.025)	(0.031)
Lagged log(average real wage)	0.026	0.120	$0.205***$	$0.200***$	$0.332***$
	(0.100)	(0.085)	(0.057)	(0.046)	(0.082)
Age	-0.006	$-0.016**$	$-0.016***$	$-0.014***$	$-0.026***$
	(0.006)	(0.007)	(0.006)	(0.005)	(0.009)
Dummy for public limited company	$-0.326**$	-0.008	0.167	$0.286***$	$0.268**$
	(0.154)	(0.161)	(0.106)	(0.088)	(0.120)
Number Shareholders	$0.111***$	$0.069**$	-0.001	-0.041	-0.049
	(0.028)	(0.031)	(0.031)	(0.032)	(0.060)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.610	0.681	0.699	0.690	0.629
Observations	1838	1838	1838	1838	1838
Units	482	482	482	482	482
Objective Function	0.148	0.253	0.303	0.244	0.142
Parente-Santos Silva test	19.674	23.551	28.297	27.136	28.237
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 4: Regressions of logged productivity introducing total shareholdings

spectively (Castelnovo *et al.* (2019), Scheffler *et al.* (2013)). All the dummies are corrected for indirect ownership as already pointed out previously. In every specification, the dummy is significantly negative, suggesting that publicly owned companies have a by around 32.7-58.5% lower productivity. Impacts are larger in higher quantiles implying that the effects are more relevant at the right tail of the distribution, as relevant firms have more to lose. Concerning the controls, the same conclusions are drawn.

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings > 0	−0.334∗∗∗	−0.420∗∗∗	−0.439∗∗∗	−0.420∗∗∗	−0.451∗∗∗
	(0.118)	(0.089)	(0.067)	(0.081)	(0.089)
Lagged log(real total assets)	0.018	−0.026	−0.033	−0.054∗∗	−0.087∗∗
	(0.029)	(0.024)	(0.025)	(0.026)	(0.039)
Lagged log(average real wage)	0.122	0.173∗∗	0.226∗∗∗	0.223∗∗∗	0.360∗∗∗
	(0.091)	(0.079)	(0.061)	(0.047)	(0.080)
Age	−0.007	−0.015∗∗	−0.012∗∗∗	−0.015∗∗∗	−0.022∗∗∗
	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)
Dummy for public limited company	−0.339∗∗	−0.016	0.163∗	0.251∗∗∗	0.234∗∗
	(0.161)	(0.123)	(0.093)	(0.089)	(0.104)
Number Shareholders	0.129∗∗∗	0.092∗∗∗	0.036	0.044	0.101∗∗
	(0.027)	(0.030)	(0.034)	(0.045)	(0.051)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.636	0.700	0.715	0.710	0.657
Observations	1932	1932	1932	1932	1932
Units	504	504	504	504	504
Objective Function	0.146	0.249	0.301	0.245	0.143
Parente-Santos Silva test	20.197	25.242	29.818	28.874	30.511
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000
Note:	The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are clustered at the firm-level. *p<0.1; **p<0.05; ***p<0.01				

Table 5: Regressions of logged productivity introducing dummy public firm = 1 if direct shareholdings > 0

3.2.2 Impacts on return on sales

Table 8 summarizes the results of the regressions of the return on sales-style Lerner index involving the sum of direct shareholdings owned by public authorities.

Plausibly, public companies exhibit smaller return on sales, implying that relevant firms have less market power and produce less profitably. Nevertheless, impacts are similar across quantiles. If direct shareholdings increase by one percentage points, return on sales decline by 0.1 percentage point.

Besides, larger firms have more market power. Impacts, however, decrease over quantiles sug-

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings $\geq$ 10	-0.327^{***}	-0.390^{***}	-0.437^{***}	-0.420^{***}	-0.448^{***}
	(0.119)	(0.088)	(0.068)	(0.081)	(0.089)
Lagged log(real total assets)	0.019	-0.027	-0.034	-0.054^{**}	-0.086^{**}
	(0.029)	(0.025)	(0.026)	(0.026)	(0.039)
Lagged log(average real wage)	0.125	0.185^{**}	0.228^{***}	0.224^{***}	0.360^{***}
	(0.091)	(0.074)	(0.053)	(0.048)	(0.080)
Age	-0.007	-0.014^{**}	-0.012^{***}	-0.015^{***}	-0.022^{***}
	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)
Dummy for public limited company	-0.340^{**}	-0.028	0.161^{*}	0.251^{***}	0.230^{**}
	(0.155)	(0.130)	(0.094)	(0.089)	(0.103)
Number Shareholders	0.128^{***}	0.087^{***}	0.036	0.045	0.102^{**}
	(0.026)	(0.027)	(0.033)	(0.046)	(0.050)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.646	0.701	0.715	0.709	0.656
Observations	1932	1932	1932	1932	1932
Units	504	504	504	504	504
Objective Function	0.146	0.249	0.301	0.245	0.143
Parente-Santos Silva test	20.418	24.791	29.778	28.736	30.126
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 6: Regressions of logged productivity introducing dummy public firm = 1 if direct shareholdings $\geq$ 10

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings ≥ 50	−0.374∗∗∗	−0.450∗∗∗	−0.509∗∗∗	−0.551∗∗∗	−0.585∗∗∗
	(0.131)	(0.085)	(0.065)	(0.079)	(0.101)
Lagged log(real total assets)	0.015	−0.024	−0.035	−0.056∗∗	−0.084∗∗∗
	(0.030)	(0.022)	(0.025)	(0.025)	(0.032)
Lagged log(average real wage)	0.118	0.166∗∗	0.210∗∗∗	0.211∗∗∗	0.351∗∗∗
	(0.107)	(0.081)	(0.055)	(0.051)	(0.075)
Age	−0.008	−0.017∗∗	−0.014∗∗∗	−0.017∗∗∗	−0.023∗∗∗
	(0.007)	(0.007)	(0.004)	(0.004)	(0.007)
Dummy for public limited company	−0.308∗	−0.021	0.139	0.265∗∗∗	0.240∗
	(0.161)	(0.119)	(0.099)	(0.083)	(0.123)
Number Shareholders	0.118∗∗∗	0.073∗∗∗	0.017	−0.006	0.007
	(0.035)	(0.027)	(0.027)	(0.041)	(0.044)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.639	0.702	0.719	0.711	0.655
Observations	1932	1932	1932	1932	1932
Units	504	504	504	504	504
Objective Function	0.145	0.248	0.298	0.241	0.141
Parente-Santos Silva test	20.989	24.418	29.016	29.187	31.537
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000
Note:	The dependent variable is $log(TFP)$ in all specifications. All standard errors, in parenthesis, are clustered at the firm-level. *p<0.1; **p<0.05; ***p<0.01				

Table 7: Regressions of logged productivity introducing dummy public firm = 1 if direct shareholdings ≥ 50

gesting that less profitable firms' return on sales benefits more from firm growth than the ones of more profitable firms. Coefficients are interpreted as semi-elasticities given the level-log specification, i.e. if the variable rises by 1%, markups rise by 0.02-0.03 percentage points. More human capital drops the return on sales. First, higher costs worsen firms' profitability. Second, the resulting productivity gains allow firms to undercut competitors, implying lower margins. Effects diminish over quantiles, since for firms with lower market power the effect of undercutting will be more relevant, while for firms with higher market power undercutting is less relevant than the higher costs. If the variable rises by 1%, return on sales drop by 0.018-0.131 percentage points. The other variables, however, do not significantly affect the return on sales.

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Direct Shareholding	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged log(real total assets)	0.034∗∗∗	0.033∗∗∗	0.030∗∗∗	0.026∗∗∗	0.019∗∗∗
	(0.004)	(0.006)	(0.005)	(0.007)	(0.007)
Lagged log(average real wage)	−0.108∗∗∗	−0.131∗∗∗	−0.120∗∗∗	−0.045∗∗∗	−0.018∗∗∗
	(0.010)	(0.025)	(0.020)	(0.010)	(0.006)
Age	−0.001	−0.001	−0.003	−0.003∗	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Dummy for public limited company	−0.026	−0.038	−0.044∗	−0.019	−0.001
	(0.020)	(0.026)	(0.026)	(0.027)	(0.019)
Number Shareholders	0.006	0.009	0.009	0.012∗	0.004
	(0.010)	(0.009)	(0.013)	(0.007)	(0.005)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.391	0.462	0.509	0.460	0.414
Observations	1865	1865	1865	1865	1865
Units	499	499	499	499	499
Objective Function	0.030	0.061	0.080	0.059	0.030
Parente-Santos Silva test	20.502	27.782	33.327	34.564	33.641
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000
Note:	The dependent variable is LI (ROS) in all specifications. All standard errors, in parenthesis, are clustered at the firm-level. *p<0.1; **p<0.05; ***p<0.01				

Table 8: Regressions of return on sales introducing direct shareholdings

The same conclusions are drawn when employing the publicly owned total shareholdings, as described in *Table* 9.

When introducing the dummies for publicly owned companies the same conclusions are drawn, as shown by *Tables* 10, 11, and 12. In every specification, the dummy is significantly negative, implying that public companies have a by around 5.6-8.9 percentage points lower return on sales.

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Total Shareholding	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗	−0.001∗∗∗
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged log(real total assets)	0.035∗∗∗	0.035∗∗∗	0.032∗∗∗	0.028∗∗∗	0.020∗∗∗
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
Lagged log(average real wage)	−0.109∗∗∗	−0.138∗∗∗	−0.125∗∗∗	−0.046∗∗∗	−0.019∗∗∗
	(0.010)	(0.024)	(0.021)	(0.011)	(0.007)
Age	−0.000	−0.001	−0.003	−0.003∗	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Dummy for public limited company	−0.029	−0.039	−0.048∗	−0.023	0.002
	(0.021)	(0.028)	(0.029)	(0.027)	(0.020)
Number Shareholders	0.001	0.006	0.007	0.010	0.004
	(0.015)	(0.011)	(0.020)	(0.008)	(0.004)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.391	0.457	0.509	0.458	0.412
Observations	1771	1771	1771	1771	1771
Units	477	477	477	477	477
Objective Function	0.031	0.062	0.082	0.060	0.030
Parente-Santos Silva test	22.214	27.712	32.463	32.985	31.651
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is LI (ROS) in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 9: Regressions of return on sales introducing total shareholdings

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings > 0	−0.056∗∗∗	−0.057∗∗∗	−0.067∗∗∗	−0.056∗∗∗	−0.076∗∗
	(0.017)	(0.016)	(0.020)	(0.021)	(0.034)
Lagged log(real total assets)	0.033∗∗∗	0.033∗∗∗	0.031∗∗∗	0.027∗∗∗	0.020∗∗∗
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
Lagged log(average real wage)	−0.101∗∗∗	−0.131∗∗∗	−0.121∗∗∗	−0.045∗∗∗	−0.019∗∗∗
	(0.014)	(0.021)	(0.020)	(0.011)	(0.007)
Age	−0.001	−0.001	−0.003	−0.003∗	−0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
Dummy for public limited company	−0.023	−0.032	−0.052∗	−0.019	0.003
	(0.022)	(0.024)	(0.027)	(0.028)	(0.020)
Number Shareholders	0.012	0.014	0.018	0.016∗∗	0.009
	(0.011)	(0.009)	(0.013)	(0.008)	(0.006)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.396	0.458	0.510	0.459	0.417
Observations	1865	1865	1865	1865	1865
Units	499	499	499	499	499
Objective Function	0.030	0.061	0.081	0.059	0.030
Parente-Santos Silva test	21.137	27.530	32.497	33.622	33.505
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is LI (ROS) in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 10: Regressions of return on sales introducing dummy public firm = 1 if direct shareholdings > 0

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings $\geq$ 10	$-0.056{*}{*}{*}$	$-0.058{*}{*}{*}$	$-0.065{*}{*}{*}$	$-0.056{*}{*}{*}$	$-0.076{*}{*}$
	(0.017)	(0.015)	(0.020)	(0.021)	(0.033)
Lagged log(real total assets)	$0.033{*}{*}{*}$	$0.033{*}{*}{*}$	$0.031{*}{*}{*}$	$0.027{*}{*}{*}$	$0.020{*}{*}{*}$
	(0.004)	(0.005)	(0.005)	(0.006)	(0.007)
Lagged log(average real wage)	$-0.101{*}{*}{*}$	$-0.132{*}{*}{*}$	$-0.121{*}{*}{*}$	$-0.045{*}{*}{*}$	$-0.019{*}{*}{*}$
	(0.014)	(0.021)	(0.021)	(0.011)	(0.007)
Age	-0.001	-0.001	-0.003	$-0.003{*}$	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Dummy for public limited company	-0.023	-0.034	$-0.053{*}{*}$	-0.019	0.002
	(0.022)	(0.024)	(0.027)	(0.028)	(0.020)
Number Shareholders	0.012	0.014	0.017	$0.016{*}$	0.009
	(0.011)	(0.009)	(0.013)	(0.008)	(0.006)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.396	0.459	0.510	0.459	0.417
Observations	1865	1865	1865	1865	1865
Units	499	499	499	499	499
Objective Function	0.030	0.061	0.081	0.059	0.030
Parente-Santos Silva test	21.578	27.791	32.670	33.537	33.993
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is LI (ROS) in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 11: Regressions of return on sales introducing dummy public firm = 1 if direct shareholdings $\geq$ 10

	Q = 0.10	Q = 0.25	Q = 0.50	Q = 0.75	Q = 0.90
	(1)	(2)	(3)	(4)	(5)
Dummy direct shareholdings $\geq$ 50	$-0.069***$	$-0.068***$	$-0.077***$	$-0.069***$	$-0.089***$
	(0.017)	(0.016)	(0.021)	(0.024)	(0.028)
Lagged log(real total assets)	$0.034***$	$0.033***$	$0.031***$	$0.027***$	$0.019***$
	(0.004)	(0.006)	(0.005)	(0.007)	(0.007)
Lagged log(average real wage)	$-0.107***$	$-0.128***$	$-0.121***$	$-0.045***$	$-0.018***$
	(0.010)	(0.028)	(0.020)	(0.010)	(0.006)
Age	-0.001	-0.001	-0.003	$-0.003*$	-0.002
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Dummy for public limited company	-0.026	-0.040	$-0.046*$	-0.020	0.002
	(0.020)	(0.026)	(0.027)	(0.026)	(0.018)
Number Shareholders	0.007	0.009	0.007	$0.012*$	0.003
	(0.010)	(0.008)	(0.014)	(0.007)	(0.005)
Nested time dummies	*yes*	*yes*	*yes*	*yes*	*yes*
R-squared	0.392	0.464	0.510	0.461	0.414
Observations	1865	1865	1865	1865	1865
Units	499	499	499	499	499
Objective Function	0.030	0.061	0.080	0.059	0.030
Parente-Santos Silva test	21.112	27.597	33.584	34.080	33.184
p-Value Parente-Santos Silva test	0.000	0.000	0.000	0.000	0.000

Note: The dependent variable is LI (ROS) in all specifications. All standard errors, in parenthesis, are clustered at the firm-level.

*p<0.1; **p<0.05; ***p<0.01

Table 12: Regressions of return on sales introducing dummy public firm = 1 if direct shareholdings $\geq$ 50

3.3 Discussion

An overriding goal of energy policy is to improve allocative and technical efficiency. This industry is traditionally characterized by widespread public ownership that is associated with efficiency losses. Especially in post-communist countries are interesting due to their history, as they have transitioned from socialist economies, dominated by large public companies, to market economies. This study sheds light on whether public firms of the electricity, and steam and air conditioning industries operate more efficiently than their private counterparts combining the frameworks by Castelnovo *et al.* (2019) and Del Bo (2013). Public firms produce less profitable and have lower market power, as they also pursue goals other than profit maximization. In higher deciles of the productivity distribution, larger firms suffer from a lower productivity, while they have higher market power, suggesting X-inefficiencies. Human capital, as measured by average real wages per employee, boost technical efficiency and drop market power and profitability, as resulting productivity gains allow firms to undercut competitors. Older firms produce less efficiently and less profitable. Generally, public limited companies are more productive and profitable than private limited companies. The effect increases with the quantile. The number of shareholders raises productivity, but only for less efficient firms. Firms with higher Lerner indexes, however, lose market power and profitability, if the number of shareholders rises.

This research contributes to the available literature by not only estimating the effects of public ownership employing dummy variables, but also using the sum of direct and total shareholdings owned by domestic public authorities, representing a novelty with respect to the previous literature (Castelnovo *et al.* (2019), Borghi *et al.* (2016)). Second, I derive productivity differentials across productivity quantiles. Third, effects on Lerner indexes are also examined.

However, one set of econometric issues is caused by employing deflated monetary values of inputs instead of quantities. Potential differences in input prices across firms, resulting from differences in the access to input markets or monopsony positions, might cause the so-called 'input price bias'. As common in the literature, I implicitly assume that all firms, private and public firms, face the same input prices. Nonetheless, my estimates indeed suffer from input price biases, in case of input price differences. Particularly, I only rely on one deflated monetary input, capital, potentially causing biased coefficients, while labour is measured physically. The input price bias results in a negative bias of coefficients, while calculated productivity, consequently, is biased upwards (De Loecker & Goldberg (2014)).

Next, another set of econometric issues stems from using deflated monetary values of output instead of quantities, called 'omitted price variable bias'. Unfortunately, price indices are only available at some industry-level, while firm-level or even product-level price indices would be required, though mostly not available. Applying industry-level price indices to firm-level operating revenues results in biased coefficients of the production function, if firm- or product-level prices deviate from the development of the industry-level price index, which are captured by the error term. The direction of each coefficient's bias is not straightforward and can go in either direction (De Loecker (2007b), De Loecker & Goldberg (2014), Klette & Griliches (1996)). To solve this problem, in the spirit of Klette & Griliches (1996), De Loecker (2007b) proposes a framework, based on including industry-specific aggregate demand shifters, which, however, fails to correctly identify the coefficients, because multiplying all asymmetrically biased input coefficients with a constant cannot yield unbiased input coefficients (Ornaghi (2006)).

Moreover, public ownership can only be captured to a limited degree, because direct and total shareholdings only provide data on the owners at the lowest stage of the ownership pyramid and, therefore, do not coincide with ultimate ownership. For instance, although the ultimate owner of a given company is a public authority, it could be classified as private firm, as it is owned by the public authority through a chain of private firms, resulting in upwards biased coefficients. Castelnovo *et al.* (2019) tackle this issue by considering the type of the global ultimate owner when defining the dummies for publicly owned firms, i.e.: the dummy is one, if shareholdings owned by public authorities exceed 10% or a public authority is flagged as global ultimate owner. Although Orbis provides data on ultimate owners, there are two disadvantages. First, data are provided as time-invariant variables. Hence, defining the binary variables the same way eliminates variation, because relevant transactions are excluded, i.e.: the public authority being the global ultimate owner sells some shares to a private investor. Second, direct and total shareholdings of the ultimate owner suffer from missing values, though owner type and country are available.

Last, selection could imply biased estimates, as public ownership serves as a tool to regulate the industry. In other words, firms might not randomly be publicly owned. If governments would systematically pick lowly productive firms, then estimated coefficients suffer from negative biases. Consequently, derived coefficients represent lower bounds of the impacts in question (Angrist & Pischke (2009)). A possible solution to this issue could be a quantile-2SLS regression instrumenting public ownership with the number of shareholders.

4 Conclusion

This paper examines the impacts of public ownership on productivity and Lerner indexes of Central European post-communist electricity (D351) and steam and air conditioning (D353) sectors. Although a long-held proposition claims that public firms produce less efficiently and profitably. Besides, analysing energy sectors is of particular interest, because they are still highly concentrated, although they have been liberalized (e.g. elimination of market barriers, vertical disintegration, privatization) fostering competition. Furthermore, examined countries are post-communist experiencing major institutional changes and liberalizations, although the government's influence in these countries is still pervasive. Especially post-communist countries are characterized by strong entry barriers aggravating the transition to well-functioning market economies. Furthermore, instead of creating open and contestable markets, poorly implemented privatisations established legal monopolies strengthening market barriers (Buccirossi & Ciari (2018)). To establish a link between public ownership and technical efficiency and market power, I employ a two-staged framework. In the first stage, I estimate a two-input value added-based translog production functions with the algorithm by Ackerberg *et al.* (2015), using a dataset on energy firms from 2009 to 2017, to obtain productivity. In the second stage, productivity is regressed on firm-level public ownership and control variables applying quantile regression to derive more precise conclusions on the link between the variables of interest. Firm-level Lerner indexes are measured by the return on sales-style.

Supporting the literature, the results show that public firms indeed produce less efficiently than their private pendants. Furthermore, differentials are plausibly larger at the right tail of the productivity distribution. Concerning Lerner indexes, public companies are less profitable given the smaller productivity and the relationship to policy makers. Highly productive firms suffer from productivity losses when firm size grows, while firm size increases markups, especially on the right tail of the markup distribution. The result suggest that firm size can indeed be a source of managerial slack. Human capital boosts technical efficiency, particularly of already efficient firms. On the other hand, resulting productivity gains allow to undercut competitors implying lower Lerner indexes and profitability. Older firms produce less efficiently and less profitable. Generally, public limited companies are more productive and profitable than private limited companies. The effect increases with the quantile. The number of shareholders raises productivity, but only for less efficient firms. Firms with higher Lerner indexes, however, lose market power and profitability, if the number of shareholders rises.

Policy makers, intending to restructure energy markets, should, therefore, continue privatisations, foster market liberalization and eliminate further entry barriers. For instance, politicians may facilitate price comparisons and encourage consumers to switch suppliers more frequently. Besides, governments may support public-private partneships, limit the influence of politicians and other interest groups on state-owned companies, and implement strict instead of soft budget constraints to improve productivity and profitability. Furthermore, organisational complexity and bureaucracy should be reduced, while improving transparency in decision-making processes. Nevertheless, particular liberalization policies such as vertical disintegration come with a cost, as economies of scope disappear, implying that efficiency losses may exceed productivity gains of fiercer competition (Gugler *et al.* (2017)).

Appendices

L The method by Ackerberg/Caves/Frazer

Unlike Olley & Pakes (1996) and Levinsohn & Petrin (2003), Ackerberg *et al.* (2015) allow for a dynamic specification in the choice of labour by claiming that labour also depends on unobserved productivity. Hence, the coefficients of free variables (e.g. labour) cannot be correctly identified in the first stages of Olley & Pakes (1996) and Levinsohn & Petrin (2003). Instead, the coefficients are estimated in the second stage. To get the intuition, imagine a subperiod between periods $t-1$ and t. First, the firm chooses the optimal amount of material. Second, the productivity shock occurs in the subperiod. Third, the amount of labour is purchased. Now, labour is an element of the demand function for material in period t, which is still invertible as long as m is strictly increasing in productivity.

In the first stage, I run

$$y_{i,t} = \phi_{i,t}(l_{i,t}, k_{i,t}) + \psi_{i,t} \tag{L.1}$$

to obtain estimates for the expected output $\hat{\phi}_{i,t}$ and the productivity shock $\hat{\psi}_{i,t}$. The expected output is

$$\begin{aligned} \phi_{i,t} = &\beta_k \cdot k_{i,t} + \beta_l \cdot l_{i,t} + \\ &\beta_{kk} \cdot k_{i,t}^2 + \beta_{ll} \cdot l_{i,t}^2 + \\ &\beta_{kl} \cdot k_{i,t} \cdot l_{i,t} + h_t^{-1}(m_{i,t}, k_{i,t}) \end{aligned} \tag{L.2}$$

with $h^{-1}(.)$ being the inverted demand for material. Assuming that the demand for material is strictly monotonically increasing in productivity allows to invert the demand function to obtain productivity as a function of the proxy and state variable. Unobserved productivity ω is substituted with the inverted function in equation (L.2).

In the second stage, estimates for all production function coefficients $\beta = (\beta_k, \beta_l, \beta_{kk}, \beta_{ll}, \beta_{kl})$ are calculated by relying on the law of motion of productivity

$$\omega_{i,t} = g_t(\omega_{i,t-1}) + \xi_{i,t} \tag{L.3}$$

using equation (L.4).

$$
\begin{aligned}
\omega_{i,t}(\beta) = & \phi_{i,t} - \beta_k \cdot k_{i,t} - \beta_l \cdot l_{i,t} - \\
& \beta_{kk} \cdot k_{i,t}^2 - \beta_{ll} \cdot l_{i,t}^2 - \\
& \beta_{kl} \cdot k_{i,t} \cdot l_{i,t}
\end{aligned}
\tag{L.4}
$$

Non-parametrically regressing $\omega(\beta)$ on its lag recovers the innovations to productivity ξ, required to form moment conditions, used to estimate the coefficients β with GMM. To obtain the standard errors of β, I rely on cluster bootstrapping.

$$
\begin{aligned}
E[\xi_{i,t} \cdot k_{i,t}] &= 0 \\
E[\xi_{i,t} \cdot l_{i,t-1}] &= 0 \\
E[\xi_{i,t} \cdot k_{i,t}^2] &= 0 \\
E[\xi_{i,t} \cdot l_{i,t-1}^2] &= 0 \\
E[\xi_{i,t} \cdot k_{i,t} \cdot l_{i,t-1}] &= 0
\end{aligned}
\tag{L.5}
$$

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