The impact of electricity prices on European manufacturing jobs

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Abstract

Increased investment in clean electricity in combination with a rising cost of carbon will most likely lead to higher electricity prices. We examine the impact from changing electricity prices on European manufacturing employment and find a negative elasticity for the most electricity intensive sectors. Since these sectors are unevenly spread across countries and regions, the negative employment impact from increasing electricity prices will also be unevenly spread. Policy makers should be well aware of this and take mitigating actions to ensure a positive public sentiment towards environment related price increases. (JEL J23, H23, Q28, Q43)

Keywords

- electricity prices
- labor demand
- employment
- manufacturing industry

1 INTRODUCTION

Many industrialized countries have committed themselves to tackling climate change and air pollution. For example, the EU has set itself a long-term goal of reducing greenhouse gas emissions by 80-95%, when compared to 1990 levels, by 2050. To achieve these goals, the share of renewable energy sources (RES) in total electricity has to rise substantially. Whilst investing in RES can have important environmental and health benefits,[1] it may increase electricity prices for firms and consumers by altering the electricity generating mix. Although the impact on the wholesale electricity price from a higher share of power generation from RES seems to be minimal,[2] RES subsidies are often recovered by levies and surcharges paid by the electricity consumer. Kreuz and Musgens (2017) calculate that Germany's "Energiewende" or energy transition incurred an annual gross cost in 2015 of €27.5 billion vs. a wholesale electricity value of €4.7 billion. The difference or RES cost is paid by electricity consumers. They calculate that ~22% of the final electricity price for private households and ~35% for industrial users is related to the Energiewende. Furthermore, rising carbon taxes, widely regarded as an efficient means to curb green gas emissions (e.g., Stiglitz et al. 2017), will most likely further increase electricity prices. Several recent studies found evidence of a high degree of pass-through of a carbon tax or emissions costs to wholesale electricity prices.[3] IMF (2019) estimates that the carbon tax needed to keeping global warming at 2°C can increase electricity prices in several European countries with ~20% by 2030.

[1] For example, the Energy Information Agency (2017) estimates that 34% of U.S. global warming emissions come from the electricity sector. Epstein et al. (2011) estimate that that public health effects of coal cost $74.6 billion annually.
[2] See e.g., Dillig et al. (2015) for Germany, Ballester and Furió (2015) for Spain, Mulders and Scholtens (2013) for The Netherlands.
[3] E.g., Fabra and Reguant (2014) for Spain, Hintermann (2016) for Germany and Lise et al. (2010) for 20 European countries.

For the manufacturing sector, energy and more particular, electricity costs are an important component of total production costs. The EU defines energy intensive sectors as sectors where energy costs amount to at least 3% of production value.[4] For the most energy intensive industries such as paper or metal production and processing the ratio can go up to 5–6 % of production cost. Germany defines companies where electricity costs surpass 14% of gross value added as electricity intensive.[5] Consequently, electricity prices can have important effects on employment and investment decisions as well. On the one hand, higher electricity prices lead to higher costs per unit of output and lower competitiveness which can translate in lower output and investment and thus lower employment. On the other hand, higher electricity prices make capital goods such as machinery more expensive relative to labor. Since labor and capital are to a limited extend substitutes (Henriksson et al. 2012), higher electricity prices can increase employment. Which of the two effects dominates is an empirical question. Nevertheless, there are legitimate concerns that a climate neutrality objective could lead to reduced competitiveness and employment via the channel of increased electricity prices.

Over the past decades, the manufacturing sector in industrialized countries has been shedding jobs at a substantial rate. The International Labour Organization (2018) estimates that EU28 countries lost approx. 8 million manufacturing jobs over the period 1995-2015. This represents a decline from 31% to 24% of the overall workforce. The main driving forces of this structural change are widely covered and studied in academic papers as well in the mainstream media, see for example Fort et al. (2018). These forces include technological progress, international trade, offshoring and outsourcing. In a neoclassical world without frictions, the decline of the manufacturing sector should not be a concern as manufacturing workers will just be reallocated to other, equally attractive jobs. However, Bijnens and Konings (2017) have shown that new

[4] Directive 2003/96 EC, OJ L283 of 31.10.2003.
[5] German Renewable Energy Sources Act or EEG (Erneuerbare Energien Gesetz).

jobs are mostly created in so called less knowledge intensive services. Higher paying manufacturing jobs are predominantly replaced by lower paying services jobs, thereby contributing to job market polarization (Goos et al. 2009). Greenstone et al. (2010) argue that retaining manufacturing jobs is important for the vibrancy of the local economy. These results show that the decline in manufacturing can have long-lasting effects, which are likely to be even larger in European economies with more rigid labor markets.

Our study investigates how electricity prices affect the employment structure of the European manufacturing industry. We thus rely on sector-level employment figures as they do not account for within-sector reallocation and purely capture sectoral shifts. We obtain country-sector-year specific electricity prices by combining data on country-level electricity prices for different consumption bands with data on the firm electricity consumption distribution per country-sector. We use these prices as an explanatory variable in our econometric model of equilibrium labor demand across countries. We estimate the electricity price elasticity of employment when output is allowed to change. Using our most strict specification, we only find negative elasticities for the most electricity intense sectors. The elasticity is around -0.05 on average and rises to -0.13 for the most industrialized countries. This implies that an electricity price increase (decrease) of 1% leads to a drop (rise) of employment of 0.05% to 0.13% for the sectors with the highest electricity intensity.

Since the share of electricity intensive manufacturing differs substantially between countries and regions, the impact of electricity price increases driven by an increased carbon tax will vary between countries and regions. We do find supportive evidence that the lost manufacturing jobs are partially compensated in the knowledge intensive services industry. These services, however, cannot necessarily absorb low skilled manufacturing workers and are not necessarily located in the same region. Policy makers must hence take into account that the burden of environmental levies on industrial electricity consumption will not be shared equally and take appropriate mitigating actions. Otherwise, electricity price shocks might cause lasting negative labor market effects, similar to the shock from Chinese import competition to the manufacturing industry, described by Autor et al. (2013). These negative and non-mitigated side effects of increasing electricity prices could reduce public support for environment related price increases.[6]

Our study relates to the broad literature on the impact of environmental regulation on competitiveness, see e.g., Dechezleprêtre and Sato (2017) for an overview. More specifically, a number of recent papers investigate the impact of electricity prices on employment directly. For the US, Kahn and Mansur (2013) find that energy-intensive industries tend to locate in low electricity price counties. They exploit county level differences in energy prices. Deschênes (2012) estimates a weakly negative relation between state level electricity prices and employment rates. Cox et al. (2014) follow a similar approach and find a weak substitutability between electricity and labor. They also estimate unconditional elasticities taking into account the output effects and find that higher input electricity prices lead to lower employment due to output contractions. Marin and Vona (2019) find that increasing energy prices lead to a higher demand for technicians and at the same time to a lower demand for manual workers. Marin and Vona (2021) find negative effects from rising energy prices on French manufacturing establishments, but also find these effects are to a certain extend mitigated by job reallocation between establishments of the same firm. Hille and Möbius (2019) find positive net employment effects of increasing energy prices. Their intuition is that while there might be job destruction in energy-intensive industries, these losses are more than compensated in sectors producing, installing, or consulting on energy saving or pollution abatement technologies. Saussay and Sato (2018) study the impact of energy prices on investment decisions and

[6] E.g. De Groote et al. (2020) describe how Belgian subsidies for solar panels led to increased electricity prices and as a result Belgian voters punished the incumbent government.

conclude a relative price increase does lead to increased investment from companies in the higher priced country towards the lower priced country. Barteková and Ziesemer (2019) find that a 10% increase in electricity prices leads to a decrease in net FDI inflows as a share of GDP by 0.4 to 0.60 percentage points.

Our study contributes to the literature in several ways. First, we produce estimates to what extent rising electricity prices will impact labor demand in Europe. We do this for fourteen European countries instead of focusing on one country. This can be important as firms trade off different countries when making their location and investment decisions. Moreover, this approach allows us to control better for possible confounding factors in our estimation strategy. For example, we can control for country specific shocks affecting both employment and electricity prices. Second, we construct a country-industry specific estimate for the evolution of electricity prices. This allows to accurately estimate different elasticities for different sectors depending on their electricity intensity. Most other studies use region specific prices without differentiating between industries (Kahn and Mansur 2013, Deschênes 2012). Sato et al. (2019) construct a dataset with industry specific energy prices for 48 countries, but only cover a subset of manufacturing sectors. Hille and Möbius (2019) do construct sector specific energy prices for several countries. This price, however, is based on a weighted average of different energy carriers, but the price of each energy carrier is not sector specific. We construct detailed sector specific electricity prices based on sector user profiles and electricity prices for different consumption bands. Marin and Vona (2021) do use firm specific energy prices but only work with a subsample of surveyed French manufacturing firms. We apply a similar strategy as in Cox et al. (2014) to construct sector specific prices but do not constrain ourselves to one country. Furthermore, we make a distinction between sectors based on electricity intensity.

This paper proceeds as follows. The next section explains the empirical estimation method and the data used. Section 3 presents the main econometric findings. Section 4 discusses the economic and policy implication and section 5 concludes.

2 MATERIALS AND METHODS

2.1 METHODOLOGY

Base model

We are interested in the overall impact of changing electricity prices on employment and more specifically the electricity price elasticity of industry-level labor demand. This elasticity can be broken down into 2 components, the substitution and the scale effect (Hamermesh 1993). The substitution effect captures the fact that (under a given level of output) electricity consuming capital will be substituted for labor when electricity prices increase. The scale effect represents the reduction in employment driven by lower output when increased electricity prices lead to increased sales prices.

We start from the workhorse model for empirical labor demand estimations described by Hamermesh (1993) and use a panel data regression that relates country-industry level employment in a particular time period to wage and capital stock. Wage and capital are typically the variables used in a labor demand estimation unconditional on the level of output. As we study the impact of electricity prices on labor demand, we also include the price of electricity:

$$emp_{cst} = \alpha_{cs} + \beta_{ct} + \mu_1 wage_{cst} + \mu_2 capital_{cst} + \mu_3 price_{cst} + \epsilon_{cst}. \quad (1)$$

Where emp_{cst}, $wage_{cst}$, $capital_{cst}$ and $price_{cst}$ stand for the natural logarithm of the level employment, wage, total capital stock and the electricity price in country c, in sector s, in year t. These variables are hence country-sector-year specific. The advantage of using this log-linear model is that we can interpret the coefficients μ_i as elasticities.

Since the industry level capital stock is not available, we follow Peichl and Siegloch (2012) and approximate the capital stock by the lagged value of industry level investment (year t-1) in addition to labor productivity.

Furthermore, α_{cs} accounts for country×sector fixed effects. These account for all time invariant factors that affect sectoral employment in a country. For example, proximity to a harbor, access to cheap resources, historically high or low levels of specialization towards an industry, specific government subsidies to benefit an industry, etc. This panel fixed effect also allows to control for sector specific influences such as the fact that a certain industry is hit harder by automation or offshoring to emerging countries than others.

β_{ct} represents country × year fixed effects. Year fixed effects pick up time specific characteristics that influence employment growth in all sectors and countries in a similar way. An example is the business cycle. On top of this, we also include country fixed effects, which pick up factors that vary at the country level such as taxes. The country×year fixed effects, e.g., allow to control for the fact that the business cycle has hit Spain harder than Belgium.

We also analyze potential differences in the effect of electricity prices between sectors with high electricity intensity and sectors with low intensity. The hypothesis is that the effect of the electricity price is larger in electricity intensive sectors. To this end we interact the electricity price with a dummy representing the level of the electricity intensity of the sector.

The model becomes:

$$emp_{cst} = \alpha_{cs} + \beta_{ct} + \mu_1 wage_{cst} + \mu_2 capital_{cst} + \sum_{low}^{very\ high} \mu_i price_{cst} \times EI_s + \epsilon_{cst}, \qquad (2)$$

where EI_s is a dummy variable taking the value 1 if the sector belongs to one out of four electricity intensity groups: very high, high, medium and low.

Equation (1) and (2) estimate static labor demand. Static labor demand does not consider the existence of adjustment costs. Dynamic labor demand, on the contrary, explicitly accounts for the costs associated with changing the level of employment. Adjustment costs may arise from either institutional (e.g., firing costs), economic (e.g., hiring costs, training) or technological adjustment obstacles (e.g., capital stock is rather fixed). These costs may lead to the situation that firms do not change their demand for labor after an exogenous shock (in our case a change of the electricity price) because the adjustment costs outweigh the benefits of a change of the level of employment. This will make firms to merely adjust their workforce slowly and sector level employment will be rather persistent.

Nickel (1986) models employment decisions that are made in such a manner that the firm maximizes the present value of its earnings net of adjustment cost of hiring/firing labor and shows that the dynamic demand for employment can be estimated by including the lagged value of employment. The dynamic model becomes:

$$emp_{cst} = emp_{cs,t-1} + \alpha_{cs} + \beta_{ct} + \mu_1 wage_{cst} + \mu_2 capital_{cst} + \sum_{low}^{very\ high} \mu_i price_{cst} \times EI_s + \epsilon_{cst} \tag{3}$$

Endogeneity

The electricity price could well be endogenous. Firstly, the electricity price could be correlated with a host of factors (e.g., fuel prices that impact overall economic activity, see next section) that simultaneously impact employment and hence enter the model as an omitted variable via the error term (ϵ_{cst}). Secondly, a significant part or the end user's price for electricity is driven by government levies and exemptions thereof. It therefore might well be that large, electricity intensive, sectors are able to influence the electricity price setting. Finally, firms within a sector experiencing a sudden demand increase (decrease), will increase (decrease) output (and employment) and hence electricity use. This might decrease (increase) the electricity price via the extended (decrease) use of volume discounts. This changed electricity usage pattern (driven by a change in demand and subsequently employment) might lead to a changed electricity price within the sector.

The first approach to mitigate these endogeneity concerns is the inclusion of a wide set of controls in addition to the electricity price. Next to the controls already mentioned (wage, capital, country×sector and country×year fixed effects) we will also include the price of other energy carriers (see next section). Fuel prices, via the channel of transportation costs, could represent a substantial part of the final price in the manufacturing industry and to a certain extend are correlated with electricity prices. Furthermore, large electricity users can easily switch to another energy source (predominantly natural gas) to generate electricity in situ or to generate steam used in the production process. Such firms are predominantly active in the sectors with the highest electricity intensity, i.e. basic metals (NACE 24), paper (NACE 17), coke and petrol (NACE 19) and chemicals (NACE 20). Whilst country×year fixed effects will, amongst others, cover a substantial part of the variation driven by changes of fossil fuel prices and country×sector fixed effects will absorb time-invariant sector specificities, we cannot be sure the added controls fully absorb biases associated with omitted variables.[7]

In addition to the endogeneity issues described above, a known problem of the dynamic panel model of Eq. 3 is that the demeaning process creates a correlation between regressor and error term (Nickel 1981). Like Hille and Möbius (2019), we use the standard instrumental variable estimation technique that deals with these endogeneity issues developed by Arellano and Bond (1991). The method applies a first difference transformation and simultaneously removes problems of correlated disturbances within sectors and controls for omitted variable bias, as

[7] E.g., Marin and Vona (2021) state that volume discounts vary between and within sector and not constant over time. This implies that output shocks affecting electricity prices are unlikely to be absorbed by the included controls.

well as time-invariant panel fixed effects (α_{cs}). The estimation is based on the general method of moments (GMM) and uses the lagged levels, as well as the lagged differences of the endogenous regressors as instruments. Since we are interested in the estimate of the coefficient for *price,* we treat this variable as endogenous in addition to the lagged dependent variable. Arellano and Bond's (1991) model is specified as a system of equations, one per time period, and therefore implies the use of a large set of instruments.[8] This leads to the risk these instruments are over-identified and not exogenous from the model itself. Furthermore, the use of second lags as instruments implies the absence of second order serial correlation. We will therefore also include the diagnostics tests to validate the used instruments. To avoid downward-biased standard errors, two-step standard error correction is used.

2.2 DATA

Background on electricity prices

The electricity cost for the end-user can generally be broken down into three parts that greatly differ between different consumer profiles and countries. First, the end-user has to pay for the electricity generation. Electricity is currently traded at electricity exchanges[9] where the commodity can be bought on a spot or future basis. The share of the actual commodity cost ranges from <50% to >90% of the final price depending on the user profile and location. Second, the end-user price includes a network cost. Network costs are the charges for transmitting the electricity via the grid of transmission system operators (TSO) and distribution system operators (DSO). The breakdown of the transmission market is country specific. Generally, a DSO manages a medium- to high-voltage grid and a TSO manages a high- and very high-voltage grid. An end-user will pay a different network charge depending on the

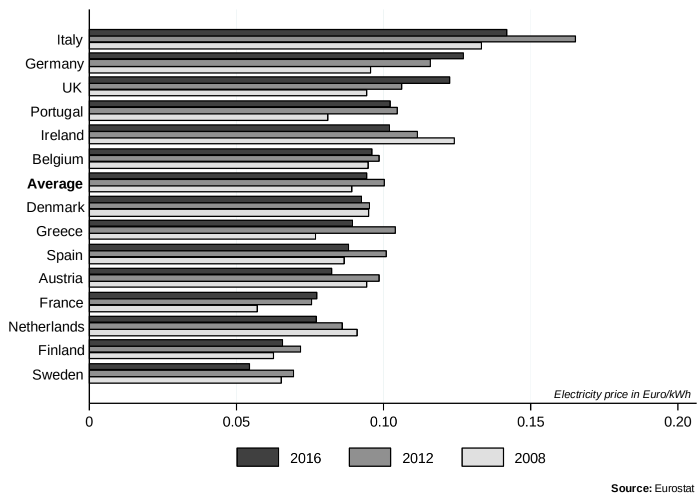
[8] The number of instruments produced is quadratic in T, the length of the timeseries available.
[9] Examples are the European Power Exchange (EPEX) and the European Energy Exchange (EEX).

voltage used. Large consumers are directly connected to the high- or very high-voltage grid and hence pay reduced or no DSO charges. Network charges are regulated and for industrial users generally are the smallest part of the end price. Finally, there is a complex system of country specific tariffs, charges, levies and exemptions thereof. These charges are characterized by a large variance and in some cases can reach twice the cost of the underlying commodity.

When we refer to electricity price in this paper, this is the final cost towards an industrial consumer, i.e. the sum of the commodity, network costs and all non-recoverable taxes and levies, excluding VAT.

Figure 1 shows the electricity prices for 14 European countries as well as the average price for the year 2008, 2012 and 2016 for a commonly used industrial consumption band. We see that prices can vary substantially. Electricity prices in Italy are approx. 3 times higher than in Sweden.

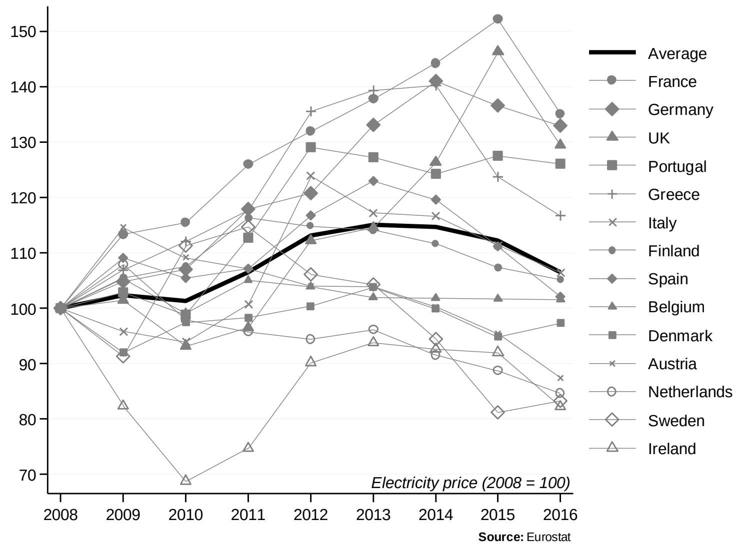
Figure 1
Electricity prices for industrial users



Note: Electricity prices (€/kWh, excl. VAT and other recoverable taxes and levies) for industrial users with a yearly consumption between 2,000 and 20,000 MWh, ranked based on 2016 price (descending).

Figure 2 shows the relative evolution of the same electricity price between 2008 and 2016. While for some countries (including Germany) the price has risen 30%~40%, for other countries the price has declined 10%~20%.

Figure 2
Relative evolution of electricity prices for industrial users



Note: Relative evolution of electricity prices (excl. VAT and other recoverable taxes and levies) for industrial users with a yearly consumption between 2,000 and 20,000 MWh. While on average we see a moderate increase, the evolution differs substantially between countries.

Data sources

We obtain information on employment and financials per sector from the structural business statistics (SBS) from Eurostat (2019a). SBS reports for each country on the structure and performance of businesses across the European Union (EU) aggregated at sectoral level using the NACE activity classification. We use yearly data on employment (full time equivalent, FTE), production value, total personnel costs, investment and value added for 24 NACE Rev. 2 manufacturing sectors (codes 10 – 33) for 14 Western European countries with a comparable level of industrialization (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Italy, Ireland, Netherlands, Portugal, Spain, Sweden and the UK). Our study covers the period 2008-

2016. Wage is calculated as total personnel cost per FTE and labor productivity as value added per FTE.

Electricity prices are gathered from the electricity price statistics for non-household consumers from Eurostat (2019b). It reports on a bi-annual basis weighted average prices for six electricity consumption bands up to 150,000 MWh and for a consumption above 150,000 MWh. Prices are very well reported for the bands up to 150,000 MWh. Price data for consumption above 150,000 MWh is not available for all countries. Prices reflect the true cost to the end-user and hence exclude VAT and other recoverable taxes and levies. Yearly prices are calculated as the average over the two six-month periods reported for each year.

The largest industrial electricity users, however, have a yearly consumption well over 150,000 MWh. For prices for these heavy users we rely on Deloitte (2018) who reports baseload and peakload prices[10] for Belgium,[11] the Netherlands, France and Germany for the period 2013-2018 for 10 consumption bands between 100,000 MWh and 1,000,000 MWh. We use these prices[12] and how they compare to the Eurostat prices as the basis to extrapolate prices for the consumption bands not reported by Eurostat. In practice the Deloitte prices reported for Belgium, France and the Netherlands for consumption of 100,000 MWh are comparable to the Eurostat prices for the highest consumption bands and then linearly decrease reaching a price that is 20%~30% lower for the highest consumption band above 950,000 MWh. We assume prices for lower bands relate to higher bands in a similar way in non -reported countries as they do on average in Belgium, France and the Netherlands. This brings us to electricity prices for

[10] We calculate the average as 35% peakload and 65% baseload. This corresponds with baseload hours on weekdays between 8h00 and 20h00.
[11] We calculate the price for Belgium as 70% Flanders and 30% Wallonia.
[12] Germany is not used for extrapolation as prices for a certain level of consumption in Germany differ significantly between one another. This is linked with the so called renewable energy surcharge (“EEG umlage”) for which certain industrial users can be exempted, not based on electricity consumption, but based on electricity intensity calculated as the ratio of electricity costs to gross added-value.

15 consumption bands per country. The exact definition of the consumption bands can be found in Appendix 1.

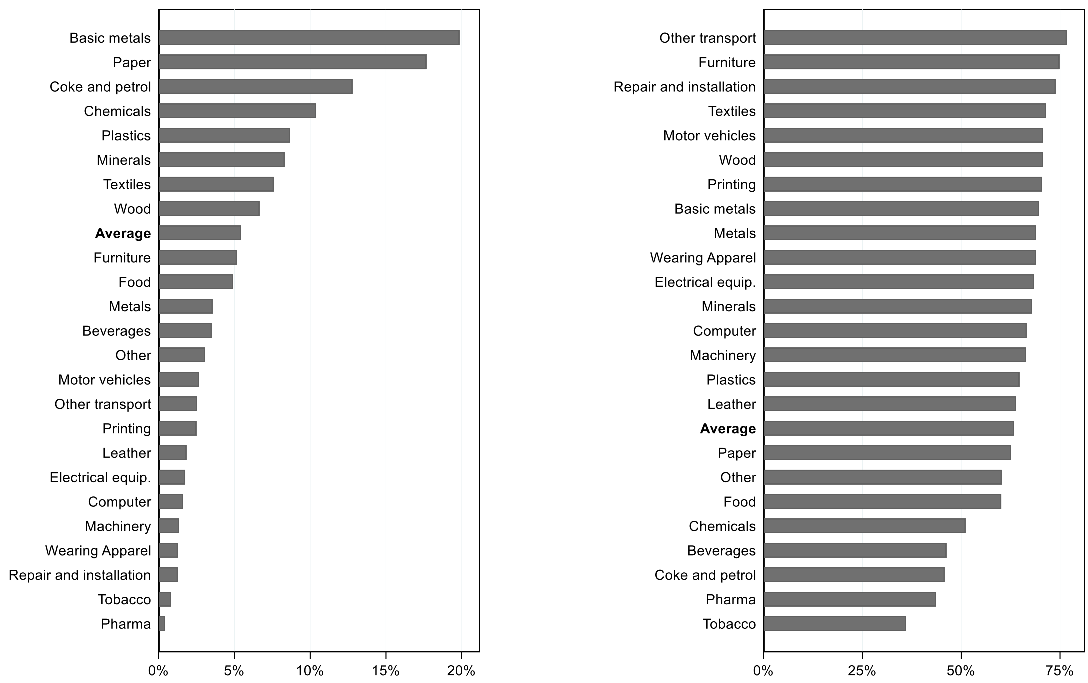
As average electricity prices are not available on the sector level, we must assume a sector level consumption profile, i.e. the share of a sector's total electricity consumption taken by each of the 15 consumption bands. For this we base ourselves on confidential data from the National Bank of Belgium on firm level energy consumption and construct a consumption profile per sector. We subsequently assume this consumption profile to be similar across countries used in our study. This is a realistic assumption since technology levels in manufacturing (with respect to electricity usage) in the most industrialized countries in Europe are comparable. To exclude gas consumption from energy consumption we base ourselves on the sector level ratios of electricity vs. gas consumption and prices from Eurostat (2019b, 2019c). This reports consumption on sector aggregation level between NACE 1-digit and NACE 2-digit. This consumption is spread over the underlying NACE 2-digit codes based on the detailed energy statistics from the German federal statistical office (Destatis 2019). The result of this exercise is the matrix reported in Appendix 2 that spreads the industry electricity consumption over the different consumption bands. Not surprisingly we see the very large electricity consumers predominantly in the coke and petrol (NACE 19), chemical (NACE 20), basic metals (NACE 24) and paper (NACE 17). The importance of this exercise is to account for the fact that the largest electricity consumers will pay the lowest prices and since the consumption distribution differs substantially between sectors, this will create electricity price variation between sectors.

Finally, we now link this sectoral consumption profile with prices per consumption band to come to these sector level electricity prices.

We categorize the different manufacturing sectors into 4 electricity intensity bins: very high, high, medium and low. This is done based on how average electricity expenditure relates to average value added. Electricity expenditure, that combines consumption and prices, is again obtained from Eurostat (2019b, 2019c) and Destatis (2019). Figure 3a gives the overview of the electricity intensity per sector. The 4 most electricity intensive industries also rely on the highest consumption bands (where prices are not reported by Eurostat). We categorized them as very high electricity intensive. The remaining 20 industries are grouped based on similarity of the electricity intensity into two groups containing 6 industries (high and medium intensity) and one group containing 8 industries (low intensity). The overview of which industry belongs to which electricity intensity bin is given in Appendix 3. Figure 3b also shows the labor intensity (personnel costs divided by value added) per sector. While electricity intensity ranges from almost zero to ~20% with an average of ~5%, labor intensity differs less between sectors with most sectors around the average of ~60%.

Figure 3

a Electricity intensity **b Labor intensity**



Note: Electricity intensity per sector calculated as the average of electricity expenditure divided by value add. Labor intensity calculated as the average of personnel costs divided by value added. More detail in Appendix 3. Source: Authors' calculations.

We have validated the results of the data exercise, sector level electricity consumption profiles and sector level electricity intensities with industry experts and perform robustness checks in section 3.3.

As we do not have information on country – sector specific gas prices, we base ourselves on Eurostat (2019e) and use country specific gas prices and take the average of the 4 highest consumption bands that are well reported.

We do not have access to country specific coal prices. We use country – year specific figures on consumption of solid fossil fuels from Eurostat (2019c) as this will be negatively correlated with the price.

Country – year specific fuel prices are gathered from the European Commission's Weekly Oil Bulletin. We use the price averaged over the year for diesel as this is most often used in the transportation sector. The price includes duties and taxes as this represents a significant part of the final price.

3 RESULTS

3.1 BASE SPECIFICATION

Error! Reference source not found. estimates the coefficients from Equations 1 to 3. Columns (1) and (2) estimate static labor demand via ordinary leased squares (OLS). Columns (3) and (4) use the Arellano-Bond method and treats the electricity price as endogenous. Columns (2) and (4) make a distinction between the electricity intensity of the sector. All columns include panel fixed effects, as well as country, year and country × year fixed effects.

The coefficient of interest is the coefficient for the *electricity price* which gives the unconditional elasticity of labor demand in function of the electricity price. When we do not discriminate between sectors based on electricity intensity, we find a value between -0.15 and -0.19. This implies an electricity price increase (decrease) of 1% will, on average, reduce (increase) labor demand 0.15% to 0.19%.[13] Cox et al. (2014) find unconditional demand elasticities between -0.06 and -0.69 depending on the skill levels of the involved labor.

The estimates for the employment – wage elasticity of -0.12 to -0.31 are on the lower side of the typical range of -0.15 to -0.75 reported by Hamermesh (1993) as we do not make a distinction between low and high skilled labor. In a more recent study, though, Lichter et al. (2015) report, based on a meta-regression analysis, point estimates for medium-term elasticities of -0.114 to -0.243, i.e. similar to the values we find. This provides us with a certain level of trust of the model and the data.

The estimates for *electricity price* based on the Arellano-Bond estimation (columns 3 and 4) are dynamic elasticities and are, as expected, lower than the static elasticities estimated based

[13] We have checked to what extend the elasticity is symmetric by using split sample regressions. The point coefficients found for the sample with year-on-year electricity price increases are higher than the ones found for the sample with year-on-year price decreases. Since the confidence intervals increase, the estimates are, however, not statistically different.

on OLS.[14] We still need to assess the validity of the instruments, the lagged levels and first differences of the endogenous regressors. Based on the result in Table 1, we cannot reject the null hypothesis of the Sargan-Hansen test for the Arrallo-Bond model. The null hypothesis assumes that the instruments, as a group, are exogenous. The instruments are hence not over identified. Furthermore, we also cannot reject the absence of 2nd order serial correlation. Thus, the diagnostics do not reject the Arellano-Bond model.

From **Error! Reference source not found.** we learn that the average elasticity for all sectors (columns 1 and 3) does not hold across all sectors (columns 2 and 4). For sectors will low electricity intensity the elasticity is around -0.09 (column 4) and for the sectors with medium and high electricity intensity the elasticity becomes higher (more negative) around -0.14 and -0.12.[15] For the sectors with the highest electricity intensity, the elasticity clearly is not different from the elasticity for the low intensity sectors. We expect the elasticity to become higher (more negative) the more electricity intense the sector is. Possibly this (surprising) result is due to the fact these sectors also make the most use of natural gas as an energy source into the production process (either directly, or via on site electricity generation plants). This possibly makes these sectors less sensitive to electricity price changes as one might expect in the absence of energy from gas.

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[14] Dynamic elasticities are short run elasticities. For the long run elasticity that incorporates adjustment costs, the value needs to be divided by 1 minus the estimate for lagged employment.

[15] Based on a one-sided Wald test $\chi^2(1)$ we can reject the hypothesis that the elasticity for low intensity is higher (more negative) or equal to the elasticity for medium intensity with p=0.04. For high intensity we can reject with p=0.14.

Table 1
Estimation results for the elasticity of employment in function of electricity prices, excluding fossil fuels

	(1) *employment*	(2) *employment*	(3) *employment*	(4) *employment*
employement$_{t-1}$			0.170*** *(0.0241)*	0.462*** *(0.0121)*
electricity price	-0.191** *(0.0654)*		-0.148** *(0.0462)*	
electricity price × low intensity		-0.151+ *(0.0844)*		-0.0930** *(0.0294)*
electricity price × medium intensity		-0.271** *(0.0840)*		-0.145*** *(0.0308)*
electricity price × high intensity		-0.250** *(0.0835)*		-0.121*** *(0.0286)*
electricity price × very high intensity		-0.167* *(0.0708)*		-0.0928*** *(0.0190)*
wage	-0.120** *(0.0457)*	-0.118** *(0.0458)*	-0.306*** *(0.0497)*	-0.284*** *(0.0168)*
investment$_{t-1}$	0.0737*** *(0.00713)*	0.0735*** *(0.00713)*	-0.00479 *(0.00527)*	-0.0155*** *(0.00247)*
labor productivity	-0.00975 *(0.0184)*	-0.00964 *(0.0184)*	-0.0787*** *(0.0139)*	-0.0565*** *(0.00477)*
Country × sector FE	yes	yes	yes	yes
Country × year FE	yes	yes	yes	yes
N	2403	2403	1769	2059
r2	0.325	0.327		
Sargan test			49 (df=39)	161.381 (df=139)
2nd order serial correlation			1.3022	1.5548

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions (1) and (2) are standard OLS panel regression, (3) and (4) are Arellano-Bond GMM regressions treating employment$_{t-1}$, electricity price and its interactions as endogenous. (3) and (4) uses two-step standard error correction.

3.2 SPECIFICATION INCLUDING FOSSIL FUELS

In the previous section we found similar elasticities for sectors with the highest electricity intensity and sectors with the lowest. This is counterintuitive as these heavy users should be hit the hardest when electricity prices increase. A possible explanation is that the very large electricity users can easily switch to gas to generate electricity in situ or to generate steam used in the production process. Furthermore, as discussed in the section on endogeneity the price of other fossil fuel sources might impact employment and could be correlated with the price of electricity. Whilst the GMM approach we use does absorb bias stemming from omitted variables, we can include other fossil fuel prices as explanatory variables into the model as well.

Table 2 shows the regression results. We again use OLS (columns 1 and 2) and the Arellano-Bond method (column 3 and 4). As in situ electricity production will be viable predominantly in the sectors with the highest electricity intensity, columns (2) and (4) only include the sector with very high electricity intensity, i.e. basic metals (NACE 24), paper (NACE 17), coke and petrol (NACE 19) and chemicals (NACE 20).

The Arellano-Bond diagnostics again do not reject the model. We now only find significant coefficients, however, for the electricity price for the sectors with the highest electricity intensity and the elasticity ranges between -0.05 and -0.08. These results are hence more in line with the intuition that the electricity price predominantly matters for the sectors that rely the most on electricity as an input factor. The coefficient for the price of gas is also in line with the intuition. On average employment is not sensitive to the gas price. For the sectors with the highest electricity intensity that can switch to in-situ electricity production, the gas price does negatively impact employment (column 4). Next to gas as a source for electricity generation, some firms in these sectors will also directly use gas as an input into the production process.

Table 2
Estimation results for the elasticity of employment in function of electricity prices, including fossil fuels

	(1) *employment*	(2) *employment*	(3) *employment*	(4) *employment*
$employement_{t-1}$			0.251***	0.290***
			(0.0107)	*(0.0470)*
electricity price × low intensity	0.0821+		0.0375	
	(0.0471)		*(0.0320)*	
electricity price × medium intensity	0.0210		-0.0395	
	(0.0452)		*(0.0380)*	
electricity price × high intensity	-0.00777		-0.0266	
	(0.0445)		*(0.0261)*	
electricity price × very high intensity	-0.0552	-0.0797*	-0.0747*	-0.0457***
	(0.0503)	*(0.0338)*	*(0.0321)*	*(0.00904)*
wage	0.161***	-0.000374	-0.0139	-0.0906***
	(0.0440)	*(0.0612)*	*(0.0342)*	*(0.0199)*
$investment_{t-1}$	0.0814***	0.00924	-0.00473	-0.00531*
	(0.00714)	*(0.00836)*	*(0.00353)*	*(0.00212)*
labor productivity	-0.0337+	-0.0204	-0.0505***	0.00444
	(0.0188)	*(0.0185)*	*(0.0119)*	*(0.00439)*
gas price	0.0132	-0.0106	0.0123	-0.0350*
	(0.0346)	*(0.0497)*	*(0.0192)*	*(0.0139)*
diesel price	-0.484***	-0.408***	0.0270	0.0701
	(0.0788)	*(0.109)*	*(0.0453)*	*(0.0843)*
coal consumption	-0.0274*	0.00202	-0.00852+	-0.00382
	(0.0120)	*(0.0175)*	*(0.00459)*	*(0.00447)*
Country × sector FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Country × year FE	no	no	no	no
N	2109	327	1532	269
r2	0.210	0.276		
Sargan test			87 (df=78)	33 (df=55)
2nd order serial correlation			0.711	1.007

Standard errors in parentheses
$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Note: Regressions (1) and (2) are standard OLS panel regression, (3) and (4) are Arellano-Bond GMM regressions treating $employment_{t-1}$, electricity price and its interactions as endogenous. (3) and (4) uses two-step standard error correction. (2) and (3) only include sectors that have a very high electricity intensity. As the fossil fuel prices are country – year specific, country × year fixed effects are not included.

3.3 Robustness checks

Electricity prices for high consumption bands above band F are extrapolated based on the prices for the very high consumption bands from Deloitte (2018). The sector level price is subsequently calculated based on the user profile of Appendix 2. We now assume that the electricity price for the consumption bands above band F (150,000 MWh) are the same as the price for band F. Band F is the highest consumption band for which Eurostat reports accurate data for all countries. We focus on the GMM specifications. The result in shown in Table 3. Column (1) retakes regression (4) from Table 1 and column (2) retakes regression (4) from Table 2. We find similar results and the Arellano-Bond diagnostics do not reject the model.

Both the consumption profile as well as the prices for the high consumption bands are based on information for Belgium. We subsequently assume that this consumption profile is the same for the 14 countries included in the analysis. If this assumption does not hold, the electricity prices used in the analysis might differ from the actual prices faced by a certain sector in a certain country. We therefore further limit the analysis to the most industrialized countries (Belgium, Germany, France, Italy, the Netherlands and Sweden) as these countries are most likely to resemble Belgium. The result is shown in Table 3. Column (3) retakes regression (4) from Table 1 and column (4) retakes regression (4) from Table 2. The coefficient in column (4) for the elasticity for the sectors with very high electricity intensity is substantially higher (more negative) compared to what we previously found for all 14 countries. The coefficient is less significant though, possibly related to the fact that the number of observations becomes smaller.

Table 3

Estimation results for the elasticity of employment in function of electricity prices, robustness check for high consumption band and consumption profile

	(1) *employment*	(2) *employment*	(3) *employment*	(4) *employment*
employement$_{t-1}$	0.444***	0.392***	0.421***	0.623***
	(0.0118)	*(0.0353)*	*(0.00416)*	*(0.165)*
electricity price × low intensity	-0.133***		-0.0515	
	(0.0294)		*(0.0409)*	
electricity price × medium intensity	-0.179***		-0.168***	
	(0.0322)		*(0.0431)*	
electricity price × high intensity	-0.155***		-0.112**	
	(0.0286)		*(0.0376)*	
electricity price × very high intensity	-0.121***	-0.0246+	-0.128***	-0.134+
	(0.0207)	*(0.0126)*	*(0.0279)*	*(0.0816)*
wage	-0.274***	-0.0965***	0.635***	-0.0561
	(0.0164)	*(0.0224)*	*(0.0244)*	*(0.0707)*
investment$_{t-1}$	-0.0138***	-0.0105***	-0.0229***	-0.0235*
	(0.00238)	*(0.00288)*	*(0.00180)*	*(0.0104)*
labor productivity	-0.0566***	0.000281	0.0267***	-0.0222
	(0.00486)	*(0.00343)*	*(0.00456)*	*(0.0181)*
gas price		-0.0266+		-0.108
		(0.0152)		*(0.263)*
diesel price		0.0877***		0.128
		(0.0212)		*(0.213)*
coal consumption		0.00984***		0.0210
		(0.00285)		*(0.0253)*
Country × sector FE	yes	yes	yes	yes
Year FE	yes	yes	yes	yes
Country × year FE	yes	no	yes	no
N	2059	276	877	138
r2				
Sargan test	91 (df=139)	28 (df=55)	94 (df=139)	7.2 (df=55)
2nd order serial correlation	0.69	1.11	94.57	0.41

Standard errors in parentheses

$^{+}$ *p < 0.10,* * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

Note: Arellano-Bond GMM regressions treating employment$_{t-1}$, electricity price and its interactions as endogenous. Sector level electricity price is calculated assuming price for consumption band F (150,000 Mwh) is valid for all consumption levels above this band. In addition (3) and (4) restrict the countries to Belgium, Germany, France, Italy, the Netherlands and Sweden.

4 Discussion

In the previous section we have shown that increasing (decreasing) electricity prices cause a loss (gain) of employment in manufacturing industries, predominantly in that part of manufacturing that is most reliant on electrical energy. For these sectors we have found elasticities around -0.05 on average and -0.13 for the most industrialized countries.

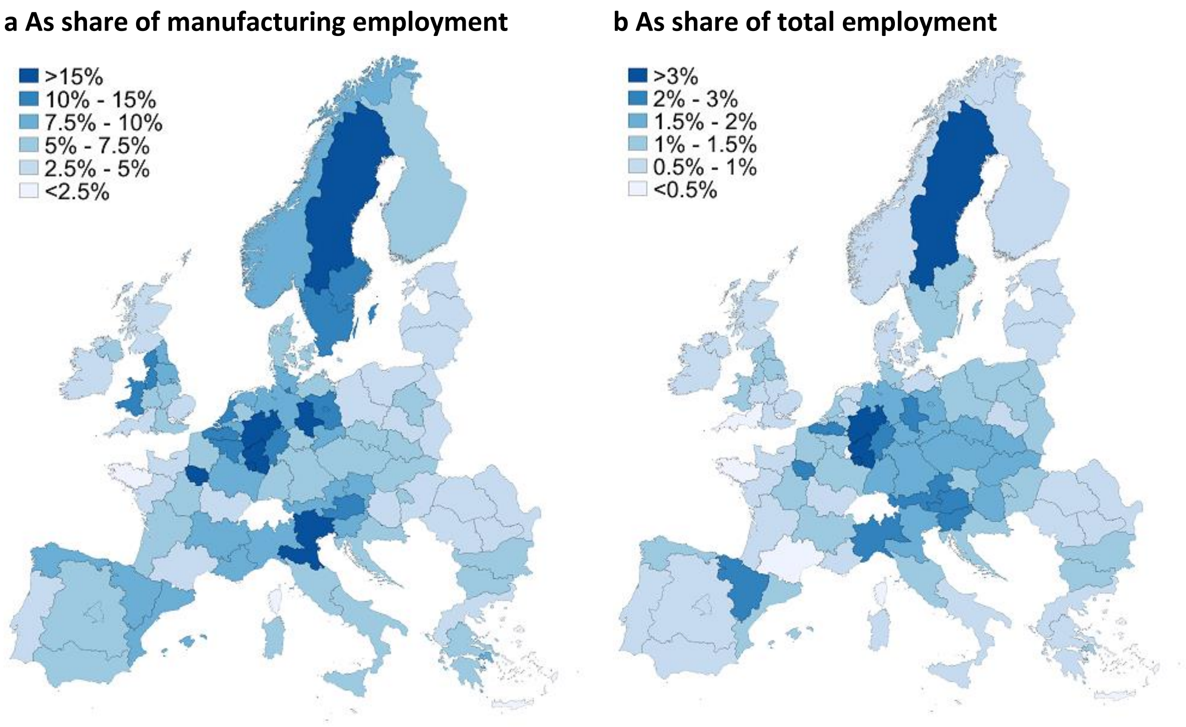
There are clear reasons to believe that electricity prices will (continue to) rise. Increasing efforts to curb climate change and air pollution will have an impact on the electricity generation mix. IMF (2019) estimates that an ambitious climate change scenario (i.e. keeping global warming at 2°C) requires a carbon tax of \$75 a ton CO_2. Under such a scenario, the IMF also estimate energy prices will rise considerably. Coal prices could typically rise by more than 200 percent as coal has a high carbon content. They expect electricity prices[16] to rise more modestly. Furthermore, the increase will vary across countries depending on the emission intensity of generation. With a \$75 a ton CO_2 carbon tax, the IMF expects electricity prices to rise with e.g., 2% in France, 18% in Germany, 18% in Italy and 16% in the UK. France will experience the lowest rise as a large part of its power generation is nuclear based.

The expected rise of electricity prices estimated by IMF (2019) could well be a lower bound as a \$75 carbon might not be sufficient to reach the set climate goals. During the unprecedented economic downturn of 2020 global CO_2 emissions only reduced with ~6% (IEA 2021). Yet, to keep global warming at the 1.5 °C or 2 °C temperature targets of the Paris Agreement, UNEP (2019) estimates that an emission reduction of respectively 7.6% and 2.7% is needed each year between 2020 and 2030. Furthermore, current carbon prices from the EU Emissions Trading System already stand at €50 a ton in June 2021, a 50% increase since the start of 2021. Based

[16] IMF (2019) discusses the impact of a carbon tax on retail electricity prices. We assume the impact on industrial electricity prices to be similar. Since the underlying commodity price represents a higher share of the industrial price, this is likely to be a lower bound for the impact.

on these insights the price of carbon could be well over $75 a ton CO2 by 2030[17] and therefore the associated electricity price increase as expected by IMF (2019) can be viewed as a lower bound estimate.[18]

Figure 4
Share of the workforce employed by very high electricity intensive sector.



Note: Geographical areas defined based on NUTS1 code. Sector specific employment figures gathered from Eurostat (2019a), total manufacturing employment and overall employment gathered from Eurostat (2019f). Figures for 2016.

Figure 4 shows the share of the workforce employed by the sectors with very high electricity intensity. Workers active within these sectors are likely to be impacted by electricity price rises. From Figure 4 we learn that each country and each region within a country will be impacted differently as energy intensive industries are not evenly distributed across countries and within

[17] The UK's Zero Carbon Commission recently advocated a £75 carbon price by 2030. Some experts come to a significantly higher price. E.g., the Quinet-2 Commission in France computed that to reach carbon neutrality by 2050, the tax should be set at €69 in 2020, raising by more than 11% each year to reach €230 in 2030 and then more slowly at a 6% rate to be settled at €750 in 2050.

[18] Specifically for Belgium, EnergyVille (2020) estimates, based on a €83 carbon price in 2030, that electricity wholesale prices could almost double, driven by the cost of investment to expand generation capacity based on renewable energy sources.

countries. The region experiencing the highest impact are located in Belgium, Germany, Netherlands, Northern Italy and Sweden.

Not only different manufacturing industries will be impacted differently by rising electricity prices, but also different types of workers will be impacted differently. Cox et al. (2014) show, based on German data, that elasticities indeed are significantly higher for low skilled workers than for high skilled ones. Combining these two insights (different impact based on sector and skill level of the employee) imply that especially low skilled workers in electricity intense sectors will disproportionally suffer from rising electricity prices.

Should one worry about this evolution? In (neoclassical) theory, these displaced workers will simply shift to other industries which is not necessarily a bad thing. Over the past decades, millions of manufacturing jobs have disappeared whilst employment rates did not significantly rise. The rise of the services industry more than compensated the lost manufacturing jobs.

This is where the so called "double dividend", introduced by Pearce (1991), comes into play. Whilst the first dividend, environmental benefits, is generally not contested, the second dividend, economic benefits, remains heavily debated, both by policy makers and by academics[19]. The second dividend implies that environmental taxes can be used to offset other more distortionary taxes that slow economic growth. The debate about the second dividend generally focuses on the direct labor market effects of the energy transition. These direct effects refer to a shift from highly capital intensive and import driven classic energy generation towards more labor intensive (and local) renewable energy generation. Environmental tax revenues should reduce other taxes which offset the negative effects from the environmental tax. Increased taxation on electricity will have a negative effect on manufacturing employment, but

[19] Freire-González (2018) surveys the literature that tests the double dividend hypothesis and finds only 55% of simulations achieve a double dividend. He concludes that the economic dividend still remains an ambiguous question that needs further research.

this can be balanced by lowering labor taxes. Doing so, it will smoothen the shift towards greener parts of the economy.

We clearly do not list nor investigate specific labor tax reductions as a compensation for manufacturing job losses stemming from increased electricity prices. We, however, turn back to the data to investigate whether we find an indication of a shift from capital intensive manufacturing to labor intensive services correlated with changing electricity prices. In Appendix 10, we link the level of employment in 3 aggregate industries (manufacturing, knowledge intensive services and less knowledge intensive services)[20] with changes of the average electricity price in the country concerned. We find a negative elasticity in line with earlier estimates for the manufacturing industry. We find a similar, though positive elasticity, for the knowledge intensive services and a non-significant or slightly negative elasticity for the less knowledge intensive services. We hence find supportive evidence of an employment shift associated with increased electricity prices away from the manufacturing industry towards knowledge intensive services. A policy concern thus remains. The hardest hit group (low skilled manufacturing workers) might experience difficulties switching to knowledge intensive services. Furthermore, these services are likely located in different regions than electricity intensive manufacturing.

[20] The services industry (NACE Rev. 2 2-digit codes 41 – 99) is divided into knowledge intensive services (KIS) and less knowledge intensive services (LKIS) according to Eurostat (2018d). We disregard the public sector (NACE 84 – 99).

5 CONCLUSION

Increasing the share of renewables in the electricity generation mix is an important lever to reduce global warming and air pollution. This will require continued and large investment in clean electricity generation capacity. The costs associated with these investments are generally borne by the end user and result in a higher electricity price. Furthermore, rising carbon taxes will most probably further increase electricity prices.

In this paper we have shown that an increased (decreased) price of electricity will lead to a reduced (increased) level of employment in the manufacturing sectors that are most reliant on electricity as an input. For sectors that are not electricity intensive we do not find an impact. We estimate the elasticity of employment with respect to the price of electricity for the electricity intensive sectors and find values of -0.05 on average and -0.13 for the most industrialized countries. To come to this conclusion we have constructed sector, year specific electricity prices for fourteen European countries. We combine this information with sector level employment and wage information and estimate a labor demand model.

Since electricity intense manufacturing is not evenly spread across countries nor regions, the impact of rising electricity prices will also be unevenly spread. Although the overall benefits from greener electricity generation are clear, some regions (with electricity intense manufacturing) and some types of workers in these regions (especially low skilled, Cox et al. 2014) could end up worse off.

We do find supportive evidence that the lost manufacturing jobs are partially compensated in the knowledge intensive services industry. These services, however, are likely to be in different geographical areas and cannot necessarily absorb low skilled manufacturing workers. Policy makers should be well aware of these consequences when additional environmental taxes are introduced. If not properly mitigated by e.g. off-setting tax decreases or transfers that directly benefit the impacted industries, regions or workers, the heterogonous labor market response of rising electricity prices could lead to a negative public sentiment towards environment related price increases.

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6 REFERENCES

Autor, D. H., Dorn, D., & Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review, 103*(6), 2121-2168. doi: 10.1257/aer.103.6.2121

Ballester, C., & Furió, D. (2015). Effects of renewables on the stylized facts of electricity prices. *Renewable and Sustainable Energy Reviews, 52*, 1596-1609.

Barteková, E., & Ziesemer, T. H. W. (2019). The impact of electricity prices on foreign direct investment: evidence from the European Union. *Applied Economics, 51*(11), 1183-1198.

Berlingieri, G. (2014). Outsourcing and the Rise in Services. CEP Discussion Paper 1199, London School of Economics.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics, 119*(1), 249-275.

Bijnens, G. & Konings, J. (2017). An Enterprise Map of Belgium. VIVES Policy Paper, KU Leuven.

Bovenberg, A. L., & Goulder, L. H. (2002). Environmental taxation and regulation. In *Handbook of public economics* (Vol. 3, pp. 1471-1545). Elsevier.

Cox, M., Peichl, A., Pestel, N., & Siegloch, S. (2014). Labor demand effects of rising electricity prices: Evidence for Germany. *Energy Policy, 75*, 266-277. doi: https://doi.org/10.1016/j.enpol.2014.10.021

Dechezleprêtre, A., & Sato, M. (2017). The impacts of environmental regulations on competitiveness. *Review of Environmental Economics and Policy, 11*(2), 183-206.

De Groote, O., Gautier, A., & Verboven, F. (2020). The political economy of financing climate policy: evidence from the solar PV subsidy programs.

Deloitte (2018). Benchmarking study of electricity prices between Belgium and neighboring countries. Downloadable from http://www.febeliec.be/data/1520414436Report%20Benchmarking%20study%20electricity%202018%20FINAL.pdf

Deschênes, O. (2012). Climate Policy and Labor Markets. In D. Fullerton & C. Wolfram (Eds.), *The Design and Implementation of U.S. Climate Policy*. Chicago: University of Chicago Press.

Destatis (2019). Energy consumption of manufacturing by selected economic branches in 2016. Downloadable from https://www-genesis.destatis.de/genesis/online

Dillig, M., Jung, M., & Karl, J. (2016). The impact of renewables on electricity prices in Germany–An estimation based on historic spot prices in the years 2011–2013. *Renewable and Sustainable Energy Reviews, 57*, 7-15.

Energy Information Agency (2017). How much of the U.S. carbon dioxide emissions are associated with electricity generation? https://www.eia.gov/tools/faqs/faq.php?id=77&t=11

EnergyVille (2020). Belgian long term electricity system scenarios. https://www.energyville.be/en/news-events/energyville-introduces-additional-energy-system-scenarios-electricity-provision-belgium

Epstein, P. R., Buonocore, J. J., Eckerle, K., Hendryx, M., Stout Iii, B. M., Heinberg, R., ... & Doshi, S. K. (2011). Full cost accounting for the life cycle of coal. *Annals of the New York Academy of Sciences, 1219*(1), 73-98.

Eurostat (2019a). Structural business statistics (SBS). Downloadable from https://ec.europa.eu/eurostat/web/structural-business-statistics

Eurostat (2019b). Electricity price statistics. Downloadable from https://ec.europa.eu/eurostat/statistics-explained/index.php/Electricity_price_statistics

Eurostat (2019c). Supply, transformation and consumption - commodity balances. Downloadable from https://ec.europa.eu/eurostat/web/energy/data/database

Eurostat (2019d). Eurostat indicators on High-tech industry and Knowledge – intensive services. Downloadable from https://ec.europa.eu/eurostat/cache/metadata/Annexes/htec_esms_an3.pdf

Eurostat (2019e). Natural gas price statistics. Downloadable from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Natural_gas_price_statistics

Eurostat (2019f). European Union Labour Force Survey. Downloadable from https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey

Fabra, N., & Reguant, M. (2014). Pass-through of emissions costs in electricity markets. *American Economic Review, 104*(9), 2872-99.

Fort, T. C., Pierce, J. R., & Schott, P. K. (2018). New Perspectives on the Decline of US Manufacturing Employment. *Journal of Economic Perspectives*, 32(2), 47-72.doi: 10.1257/jep.32.2.47

Freire-González, J. (2018). Environmental taxation and the double dividend hypothesis in CGE modelling literature: A critical review. *Journal of Policy Modeling, 40*(1), 194-223.

Goos, M., Manning, A., & Salomons, A. (2009). Job Polarization in Europe. *The American Economic Review, 99*(2), 58-63.

Greenstone, M., Hornbeck, R., & Moretti, E. (2010). Identifying agglomeration spillovers: Evidence from winners and losers of large plant openings. *Journal of Political Economy, 118*(3), 536-598.

Hamermesh, D. S. (1993). *Labor demand*. Princeton University Press.

Henriksson, E., Söderholm, P., & Wårell, L. (2012). Industrial electricity demand and energy efficiency policy: the role of price changes and private R&D in the Swedish pulp and paper industry. *Energy policy, 47*, 437-446.

Hille, E., & Möbius, P. (2019). Do energy prices affect employment? Decomposed international evidence. *Journal of Environmental Economics and Management, 96*, 1-21.

Hintermann, B. (2016). Pass-through of CO2 emission costs to hourly electricity prices in Germany. *Journal of the Association of Environmental and Resource Economists, 3*(4), 857-891.

IMF (2019). Fiscal Monitor: How to Mitigate Climate Change. International Monetary Fund. Washington.

IEA (2021), Global Energy Review: CO2 Emissions in 2020, IEA, Paris https://www.iea.org/articles/global-energy-review-co2-emissions-in-2020

International Labour Organization (2018). ILOSTAT, Key Indicators of the Labour Market. Downloadable at https://www.ilo.org/global/statistics-and-databases/lang--en/index.htm

Kahn, M. E., & Mansur, E. T. (2013). Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics*, 101, 105-114. doi:https://doi.org/10.1016/j.jpubeco.2013.03.002

Kreuz, S., & Müsgens, F. (2017). The German Energiewende and its roll-out of renewable energies: An economic perspective. *Frontiers in Energy, 11*(2), 126-134.

Lichter, A., Peichl, A., & Siegloch, S. (2015). The own-wage elasticity of labor demand: A meta-regression analysis. *European Economic Review, 80*, 94-119.

Lise, W., Sijm, J., & Hobbs, B. F. (2010). The impact of the EU ETS on prices, profits and emissions in the power sector: simulation results with the COMPETES EU20 model. *Environmental and Resource Economics, 47*(1), 23-44.

Marin, G., & Vona, F. (2019). Climate policies and skill-biased employment dynamics: Evidence from EU countries. *Journal of Environmental Economics and Management, 98*, 102253.

Marin, G., & Vona, F. (2021). The impact of energy prices on socioeconomic and environmental performance: Evidence from French manufacturing establishments, 1997–2015. European Economic Review, 135, 103739.

Mulder, M., & Scholtens, B. (2013). The impact of renewable energy on electricity prices in the Netherlands. *Renewable energy, 57*, 94-100.

Nickell, S. J. (1986). Dynamic models of labour demand. *Handbook of labor economics*, 1, 473-522.

Pearce, D. (1991). The role of carbon taxes in adjusting to global warming. *The Economic Journal, 101*(407), 938-948.

Peichl, A., & Siegloch, S. (2012). Accounting for labor demand effects in structural labor supply models. *Labour Economics, 19*(1), 129-138.

Rivers, N. (2013). Renewable energy and unemployment: A general equilibrium analysis. *Resource and Energy Economics, 35*(4), 467-485. https://doi.org/10.1016/j.reseneeco.2013.04.004

Sato, M., Singer, G., Dussaux, D., & Lovo, S. (2019). International and sectoral variation in industrial energy prices 1995–2015. *Energy Economics, 78*, 235-258. https://doi.org/10.1016/j.eneco.2018.11.008

Saussay, A., & Sato, M. (2018). The impacts of energy prices on industrial foreign investment location: Evidence from global firm level data. *Centre for Climate Change Economics and Policy Working Paper 344.*

Stiglitz, J. E., Stern, N., Duan, M., Edenhofer, O., Giraud, G., Heal, G. M., ... & Shukla, P. R. (2017). Report of the high-level commission on carbon prices.

UNEP (2019). Emissions Gap Report 2019. United Nations Environment Programme, Nairobi.

7 APPENDIX

Appendix 1 – Definition of electricity consumption bands

Band	***Yearly consumption range (in Mega Watt Hour, MWh)***
A	Below 20
B	20 – 500
C	500 – 2000
D	2,000 – 20,000
E	20,000 – 70,000
F	70,000 – 150,000
G	150,000 – 250,000
H	250,000 – 350,000
I	350,000 – 450,000
J	450,000 – 550,000
K	550,000 – 650,000
L	650,000 – 750,000
M	750,000 – 850,000
N	850,000 – 950,000
O	Above 950,000

Appendix 2 – Sectoral Electricity consumption profile (% of electricity consumption in certain band)

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O
10 Food		3%	6%	32%	35%	13%	9%	2%							
11 Beverages		1%	3%	28%	51%	16%									
12 Tobacco		7%	25%	68%											
13 Textiles		3%	8%	46%	15%	12%	15%								
14 Wearing Apparel	6%	49%	20%	25%											
15 Leather	1%	6%	2%	90%											
16 Wood		4%	5%	15%	13%	28%	35%								
17 Paper		1%	2%	11%	19%	31%	10%	6%		10%	11%				
18 Printing	1%	15%	17%	46%	21%										
19 Coke and petrol				1%	6%									30%	63%
20 Chemicals				5%	11%	11%	15%	8%	7%	1%		6%		4%	31%
21 Pharma			1%	10%	22%	2%	32%	33%							
22 Rubber and plastic		2%	6%	55%	35%	2%									
23 Minerals		1%	2%	13%	22%	28%	30%	3%							
24 Basic metals				3%	2%	4%	10%	5%	3%	7%	4%	7%	4%	9%	41%
25 Metals	1%	22%	24%	47%	6%										
26 Computer		5%	8%	51%	37%										
27 Electrical equip.		5%	7%	46%	43%										
28 Machinery		6%	8%	21%	34%	23%	7%								
29 Motor vehicles		1%	2%	18%	30%	30%	19%								
30 Other transport		3%	2%	37%	58%										
31 Furniture	1%	25%	30%	43%											
32 Other	3%	18%	11%	29%	39%										
33 Repair and installation	1%	18%	18%	35%	27%										

Appendix 3 – Electricity intensity, labor intensity and classification into electricity intensity bins

	Electricity intensity	Electricity intensity bin	Labor intensity
24 Basic metals	19.85%	Very high	69.72%
17 Paper	17.67%	Very high	62.44%
19 Coke and petrol	12.79%	Very high	46.98%
20 Chemicals	10.40%	Very high	50.43%
22 Rubber and plastic	8.66%	High	64.71%
23 Minerals	8.31%	High	67.87%
13 Textiles	7.59%	High	71.33%
16 Wood	6.65%	High	70.49%
31 Furniture	5.15%	High	74.80%
10 Food	4.90%	High	60.14%
25 Metals	3.56%	Medium	68.95%
11 Beverages	3.49%	Medium	45.04%
32 Other	3.05%	Medium	59.73%
29 Motor vehicles	2.66%	Medium	70.79%
30 Other transport	2.54%	Medium	76.53%
18 Printing	2.49%	Medium	70.48%
15 Leather	1.83%	Low	63.23%
27 Electrical equip.	1.75%	Low	68.34%
26 Computer	1.61%	Low	65.96%
28 Machinery	1.36%	Low	66.11%
14 Wearing Apparel	1.26%	Low	73.79%
33 Repair and installation	1.25%	Low	68.73%
12 Tobacco	0.82%	Low	33.03%
21 Pharma	0.42%	Low	41.76%
AVERAGE	5.42%		63.32%

Note: Electricity and labor intensity calculated as simple average over country - sector specific shares. Country - sector share calculated as total electricity expenditure or wage bill over the period 2008 - 2016 divided by total value added over the period 2008 - 2016.

Appendix 4 – Empirical test of the second dividend

	(1) *employment*	(2) *employment*
electricity price × manufacturing industry	-0.442*** *(0.121)*	-0.280* *(0.128)*
electricity price × knowledge intensive services	0.438*** *(0.122)*	0.651*** *(0.129)*
electricity price × <u>less</u> knowledge intensive services	-0.245* *(0.122)*	-0.133 *(0.128)*
wage	-0.572*** *(0.0662)*	-0.750*** *(0.0815)*
gas price		-0.0700 *(0.0937)*
diesel price		0.0366 *(0.221)*
coal consumption		0.0827** *(0.0305)*
Country × sector FE	yes	yes
Year Fixed Effect	yes	yes
N	375	321
r2	0.340	0.433

Standard errors in parentheses
$^{+}$ *p < 0.10,* * *p < 0.05,* ** *p < 0.01,* *** *p < 0.001*

- OLS panel regression estimating $emp_{cit} = \alpha_{ci} + \beta_t + \sum \mu_i price_{ct} \times industry_i + \mu_4 wage_{cit} + \mu_5 gasprice_{cit} + \mu_6 dieselprice_{ct} + \mu_7 coalconsumption_{ct} + \epsilon_{cit}$.
- emp_{cit} and $price_{cit}$ stand for the natural logarithm of employment (*emp*) and the wage (*wage*) in country *c*, in industry *i*, in year *t*. $price_{ct}$ stands for the electricity price (*price*) in country *c* in year *t.*
- We use country – time specific electricity prices which are the average of the prices for the 6 well reported bands (A to E) of Eurostat's prices.
- The electricity price is interacted with 3 industry dummies: manufacturing, knowledge intensive services (KIS) and less knowledge intensive services (LKIS). KIS and LKIS are defined at the NACE Rev. 2 2-digit level according to Eurostat (2019d).
- Regression on 2008-2016 data of Eurostat's Structural Business Statistics (Eurostat 2019a) for the same 14 countries as other regressions.