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Steelmaking Technology and Energy Prices: The Case of Germany*

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Abstract

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Key words: technology adoption and diffusion; steelmaking; electric arc furnace; comparative energy prices; ARDL model.

JEL classification: D24; O14; O33; Q49; C22.

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1. Introduction

Among heavy industries, the iron and steel sector ranks first when it comes to CO2 emissions and second when it comes to energy consumption (IEA, 2020). The two main routes for steelmaking are the basic oxygen furnace (BOF) and the electric arc furnace (EAF), which in 2019, had shares of 72% and 28% in total global crude steel production respectively. In Europe, the EAF is used almost exclusively for so-called "secondary steelmaking", as the main raw material input is steel scrap, with primary steelmaking from iron ore proceeding by the coal-intensive Basic Furnace-BOF route. As such, deep emission reductions in this sector are possible to the extent that (i) the share of secondary steelmaking in total steel production is increased, and (ii) innovative technologies such as hydrogen, carbon capture, use and storage (CCUS), bioenergy and direct electrification are deployed in combination with the EAF (IEA, 2020). The "Long-term Scenarios" (*Langfristszenarien*) project consortium, for instance, tasked by the German federal government with calculating scenarios in which long-term climate goals are achieved, has in their basis scenario for the steel sector that the share of secondary steelmaking in total steel production increases from 29% in 2020 to an extraordinary 61% in 2050; the remaining share of steel production is covered by hydrogen and methane direct-reduced iron in combination with the EAF (Fleiter et al., 2021). In every scenario, the EAF is a key technology for the energy transition.

Our goal in this article is to quantify the relationship between energy prices and the uptake (long-term) and deployment (short-term) of the EAF for secondary steelmaking using German steelmaking as a case study. We focus on energy prices since they are arguably of greatest interest to the social planner, being the direct target of policies such as carbon taxes and energy subsidies. Although several studies have attempted to identify the factors influencing the uptake of the EAF (Flues et al., 2015; Schleich, 2007; Crompton, 2001; Reppelin-Hill, 1999; Labson & Gooday, 1994), only Labson and Gooday focused exclusively on comparative energy prices; they were however unable to find any evidence of a relationship between energy prices and technology adoption. We hypothesise that one reason for this was simply the timing of the study: as we demonstrate, at least in Germany, steelmaking technology choice and energy prices first began to cointegrate in the early 90s; there was therefore likely not enough data when Labson and Gooday published their study to draw any statistically significant conclusions. Somewhat surprisingly, we were unable to locate any studies applying time-series analysis to these questions; we see our contribution as filling this literature gap as well.

The article proceeds as follows. In Section 2 we present the theoretical production-function framework and subsequent specification of our statistical model. Section 3 presents the results of the model estimation, including a forecasting application. We conclude with a discussion in Section 4.

2. Model Specification

Technical setup

We begin by assuming a Cobb-Douglas production function for both the EAF and BOF technologies

$$Q = AK^{\alpha}L^{\beta}M^{\gamma}E^{\delta}\ , \tag{1}$$

where Q is the quantity of the steel product produced, K is capital, L labour, M raw materials, E energetic inputs, $\alpha, \dots, \delta$ factor elasticities, and A total factor productivity. It is a straightforward exercise (Heathfield & Wibe, 1987) to show that the profit-maximising level of output as a function of factor prices is

$$Q^{1-\epsilon} = AP_Q^{\epsilon}\left(\frac{\alpha}{P_K}\right)^{\alpha}\left(\frac{\beta}{P_L}\right)^{\beta}\left(\frac{\gamma}{P_M}\right)^{\gamma}\left(\frac{\delta}{P_E}\right)^{\delta}\ , \tag{2}$$

where P_Q is the price of the steel product, P_i are the relevant factor prices, and $\epsilon = \alpha + \beta + \gamma + \delta$ is the elasticity of scale.[1] Given this setup for both the EAF and BOF, if we assume (i) that the costs of capital and labour P_K and P_L, and (ii) the factor elasticities $\alpha, \dots, \delta$ are identical for both technologies, we can take the ratio of the respective expressions for the profit-maximising level of output to obtain

$$\left(\frac{Q_{EAF}}{Q_{BOF}}\right)^{1-\epsilon} = \frac{A_{EAF}}{A_{BOF}}\left(\frac{P_{LONG}}{P_{FLAT}}\right)^{\epsilon}\left(\frac{P_{SCRAP}}{P_{ORE}}\right)^{-\gamma}\left(\frac{P_{ELEC}}{P_{COAL}}\right)^{-\delta}\ . \tag{3}$$

The expression is intuitive: upto a constant, the ratio of electric steel to oxygen steel production is a function of the following (cf. IEA, 2020; Labson & Gooday, 1994).

- *The price ratio of the long products to flat products.* The EAF typically produces so-called long products (beams, bars, rods), whereas the BOF produces flat products (predominantly hot-rolled sheets).
- *The price ratio of scrap to ore.* Recycling steel scrap and iron ore are the main raw material inputs for the EAF and BOF respectively.
- *The price ratio of electricity to coal.* Electricity and coal (typically coked on-site) are the main energetic inputs for the EAF and BOF respectively.

[1] This equation is ill-defined when $\epsilon = 1$, i.e. at constant returns to scale; this is the "adding-up problem" (Heathfield & Wibe, 1987). We assume that $\epsilon \neq 1$ in what follows. Future work may focus on testing this supposition.

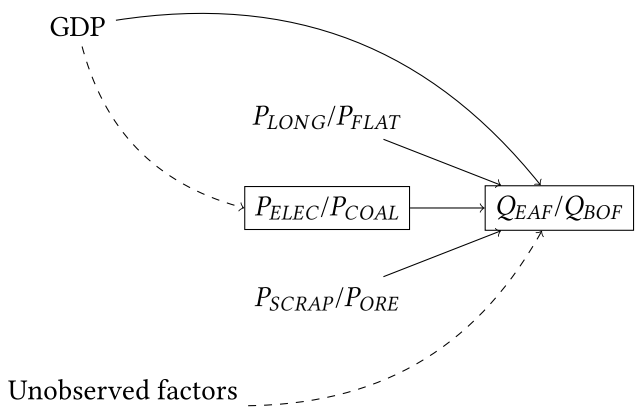

FIGURE 1. *Directed acyclical graph for the specification of the linear model. All variables in logs.*

With this equation as our starting point, we consider if any additional variables might influence steel production. Although fluctuations in steel demand should theoretically be captured by the product prices P_{LONG} and P_{FLAT}, it is conceivable that economic activity, as captured by GDP say, might contain additional information that might influence steel production. Further, steel production might also respond to other movements on the highly-competitive global steel market, such as the much-publicized instances of "dumping" (European Commision, 2016). We group these latter influences together under the label of "unobserved factors".

Specifying a linear model

Our focus is on quantifying the direct effect of energy prices on the choice of steelmaking technology; we opt for an autoregressive distributed lag (ARDL) model in order to capture any dynamic effects. Contingent on our assumptions in the previous section, Equation 3 indicates that a linear model with $\log(Q_{EAF}/Q_{BOF})$ as the endogenous variable and $\log(P_{ELEC}/P_{COAL})$ as one of the exogenous variables is appropriate. For the purposes of rigour and transparency, we investigate the inclusion of additional covariates with the help of a directed acyclical graph (DAG), as shown in Figure 1 (Textor et al., 2017).

The following conclusions are direct consequences of DAG logic (all variables in logs.)

- As long as P_{LONG}/P_{FLAT} and P_{SCRAP}/P_{ORE} have no direct influence on P_{ELEC}/P_{COAL}, it is not necessary to include them in the model. As there are no firm a priori reasons to believe that this is the case, we drop P_{LONG}/P_{FLAT} and P_{SCRAP}/P_{ORE} and focus exclusively on energy prices.
- By the same token, if GDP directly influences Q_{EAF}/Q_{BOF} and P_{ELEC}/P_{COAL}, we would have to include it ("control" for it) in the model. We indicate this possibility by a dashed arrow in the DAG.[2]

[2]Note that if the only influence of GDP on Q_{EAF}/Q_{BOF} was *through* P_{ELEC}/P_{COAL} there would be no need include it in the

- Similarly, if the "unobserved factors" which directly influence Q_{EAF}/Q_{BOF} *also* directly influence P_{ELEC}/P_{COAL}, no estimation of the effect of P_{ELEC}/P_{COAL} would be possible unless we quantified these factors and included them in our model. We assume for the purposes of this study that this is not the case; we will discuss this point further in Section 4.

In sum, as part of the analysis, we will check if there is a relationship between GDP and P_{ELEC}/P_{COAL}; this will consequently determine if the latter needs to be included as a covariate.

3. Estimation and Results

Data description

All data were obtained from the database of the Federal Statistical Office of Germany. The quantities of electric and oxygen steel produced each year are given in kilo-tonnes; their ratio is shown in Figure 2. One sees that the share of the EAF in German steelmaking has been increasing steadily over time, but seems to have plateaued in recent years. For the price of electricity, the nominal industrial producer price index (PPI) for electricity[3] was deflated with the PPI over all industrial products to produce a chained index with 2015 = 100. Similarly for the price of coal, the index of the import price of coal was deflated with the index of import prices over all products to yield a chained index with 2015 = 100. These indices were multiplied by their respective 2015 prices and the ratio taken, shown again in Figure 2; compared to the early 90s, when electricity was more than twice as expensive as coal for industrial consumers, the ratio has changed to one of increased price competitiveness. Finally, Germany's GDP (not shown) has grown steadily over the period of consideration at a average rate of 1.85% per annum from 360 bn€ in 1970 to 10 times that figure, 3.6 tn€, in 2021.

The ADF and KPSS tests were applied to check for unit root: all series were found to be $I(1)$, as can be seen in Table 1.[4]

Relationship between GDP and P_{ELEC}/P_{COAL}

As per the DAG analysis above, we first check for a relationship between log GDP and $\log(P_{ELEC}/P_{COAL})$. Given that both variables are $I(1)$, we tested for cointegration using the Engle-Granger test, concluding that the time series were not cointegrated (test statistic -1.667). We therefore took first differences and

model.

[3]For "special contract customers, high-voltage."

[4]Statistical analysis was performed with the "statsmodels" Python package (McKinney et al., 2011). Uncertainties were handled with the "uncertainties" package (Lebigot, 2022).

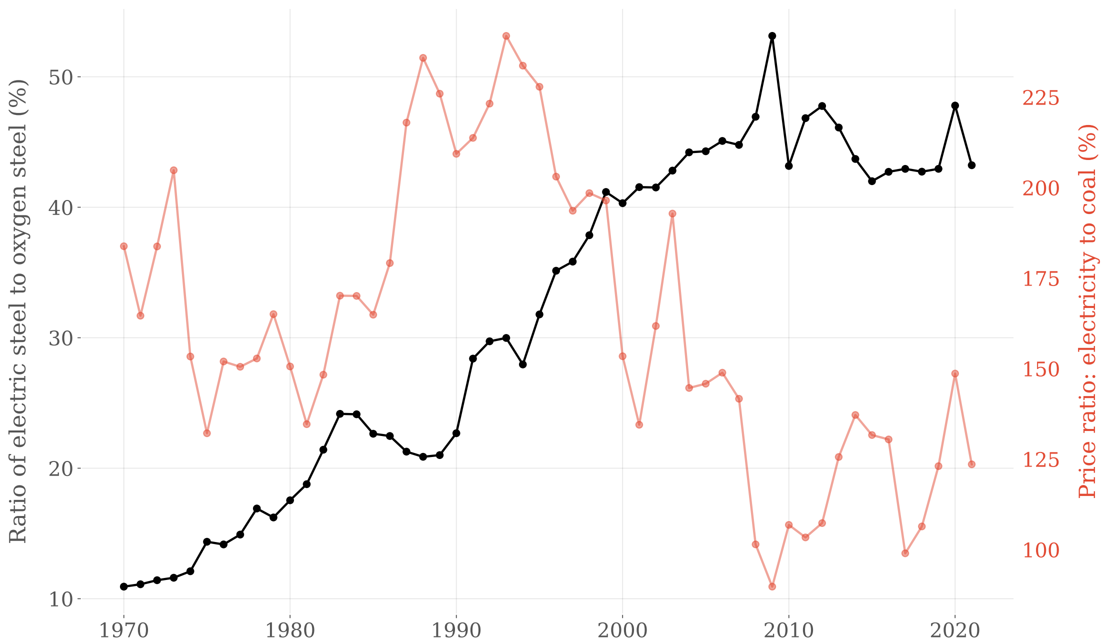

FIGURE 2. *The ratio of electric steel to oxygen steel produced in Germany, 1970–2021 (in black, left y-axis). Also depicted is the ratio of prices of electricity to coal over the same period (in red, right y-axis).*

TABLE 1. *Results of unit root testing*

Variable	ADF Test		KPSS Test	
	Test-stat.	*p*-value	Test-stat.	*p*-value
$\log(Q_{EAF}/Q_{BOF})$	-2.155	0.223	2.457	0.000
$\log(P_{ELEC}/P_{COAL})$	-1.826	0.368	1.079	0.002
log GDP	-2.476	0.121	2.621	0.000

fit an ordinary least squares (OLS) model with $\Delta \log (P_{ELEC}/P_{COAL})$ as the endogenous variable: the R^2 was identically 0, and the p-value of the coefficient of $\Delta \log \text{GDP}$ was 0.998, indicating no statistically meaningful relationship. As such, we dropped GDP from the analysis and focused exclusively on energy prices.

Cointegration analysis

Given the length of the time series at hand, it seemed appropriate to apply a rolling cointegration approach to identify changes in the cointegrating relationship between $\log (Q_{EAF}/Q_{BOF})$ and $\log (P_{ELEC}/P_{COAL})$ over time (cf. Papież & Śmiech, 2015). In particular, we wished to investigate (i) if there was any evidence of cointegration between the series extending up to the present moment, and if so, (ii) at what point in time this cointegrating relationship might have begun. Hence, beginning with the time series in its entirety, 1970–2021, we shrank the window of the Engle-Granger cointegration test one year at a time from the left endpoint, recording the ratio of the test statistic to the critical statistic at the 5 and 10% levels each time. The results are depicted in Figure 3. The evidence for cointegration clearly increases over time, becoming statistically significant beginning 1990. Figure 2 provides visual confirmation of this phenomenon.

This is a first result of the analysis thus far: there is statistical evidence that the ratio of electric steel to oxygen steel started to cointegrate with comparative energy prices beginning around 1990.[5]

The ARDL model

Given the above result, and since we wished to extract the most recent trends from the data, we restricted our ARDL(p, q) model analysis to the period beginning 1990 till the present. We fit seven models for $p, q \leq 1$ and selected the best model as per the Akaike information criterion (AIC). This turned out to be an ARDL(1, 0) model, commonly known as the "partial adjustment" or Koyck model (Boef & Keele, 2008). The estimated model was the following (standard errors in parentheses):

$$\log (\widehat{Q_{EAF}/Q_{BOF}})_t = \underset{(0.080)}{-0.2866} + \underset{(0.112)}{0.6066} \log (Q_{EAF}/Q_{BOF})_{t-1} - \underset{(0.081)}{0.1401} \log (P_{ELEC}/P_{COAL})_t \,. \tag{4}$$

The partial adjustment model is dynamic, allowing for the effects of a shock in energy prices to be distributed across time according to a speed determined by the coefficient of $\log (Q_{EAF}/Q_{BOF})_{t-1}$. In

[5] At this stage in the analysis, we once again checked the relationship between GDP and P_{ELEC}/P_{COAL} for the period 1990–2021. No evidence of cointegration was found (Engle-Granger test statistic -2.212). The p-value of the coefficient of $\Delta \log \text{GDP}$ in the OLS regression of $\Delta \log (P_{ELEC}/P_{COAL})$ on $\Delta \log \text{GDP}$ was 0.340. The analysis was thus continued without GDP.

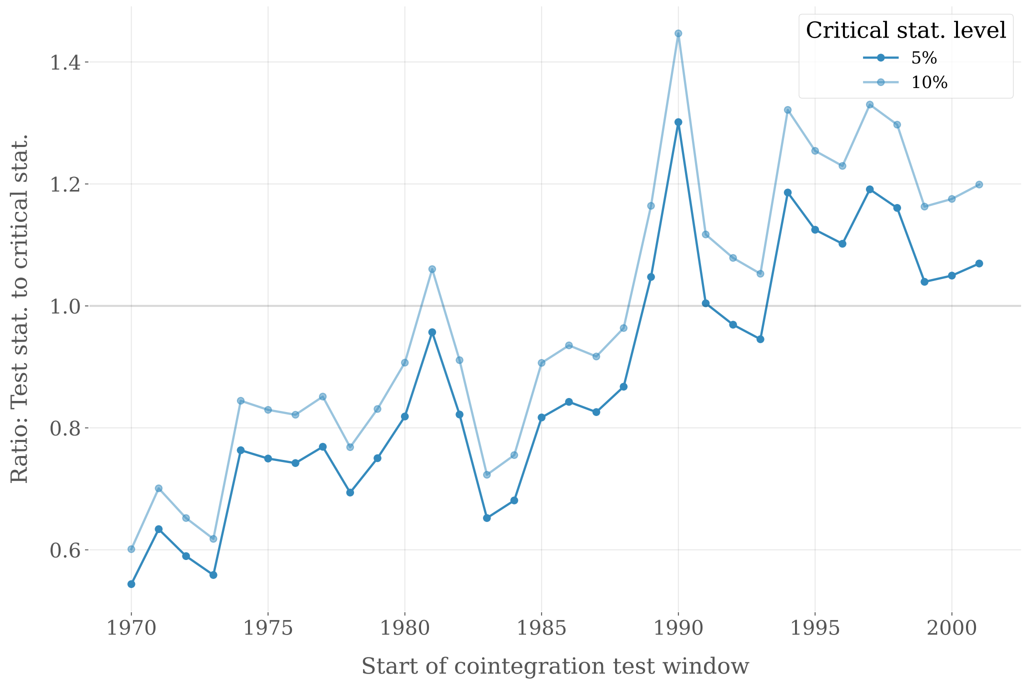

FIGURE 3. *Results of the rolling cointegration analysis.*

Figure 4, we plot the lag distribution of the model: since all variables are logged, the elasticities can be interpreted as percentages. We see that a 1% increase in P_{ELEC}/P_{COAL} leads to an immediate $(0.1401 \pm 0.086)\%$ decrease in the ratio of electric steel to oxygen steel production; at time $t + 1$, the ratio is reduced by $(0.0849 \pm 0.0369)\%$, and so on. The long-run effect is the sum over all lags, and equals $(-0.3561 \pm 0.1332)\%$, a sizeable and statistically significant effect (z-score -2.67).

We can make these numbers more concrete. First, note that since total steel production in Germany is the sum of electric steel and oxygen steel, $Q_{Tot} = Q_{EAF} + Q_{BOF}$, it is easy to convert from Q_{EAF}/Q_{BOF} to Q_{EAF}/Q_{Tot} as follows:

$$\frac{Q_{EAF}}{Q_{Tot}} = \frac{Q_{EAF}/Q_{BOF}}{1 + Q_{EAF}/Q_{BOF}} \, . \tag{5}$$

In 2021, we had $Q_{EAF}/Q_{BOF} = 43.22\%$; using the above formula, if P_{ELEC}/P_{COAL} increased 1%, the short- and long-run effects on Q_{EAF}/Q_{Tot} are $(-0.0477 \pm 0.0274)\%$ and $(-0.1213 \pm 0.0454)\%$ respectively. Given that 12 091 kt of electric steel was produced in 2021, if we assume fixed total steel production (i.e. demand must be met), the corresponding short- and long-run changes in electric steel production are (-5.77 ± 3.32) kt and (-14.67 ± 5.49) kt respectively. Since this shortfall is, in this example, compensated by the BOF, the cumulative excess emissions due to the 1% increase in P_{ELEC}/P_{COAL} is $(27.88 \pm 10.44)\ \mathrm{kt}_{CO_2}$ (emissions factors from IEA, 2020).

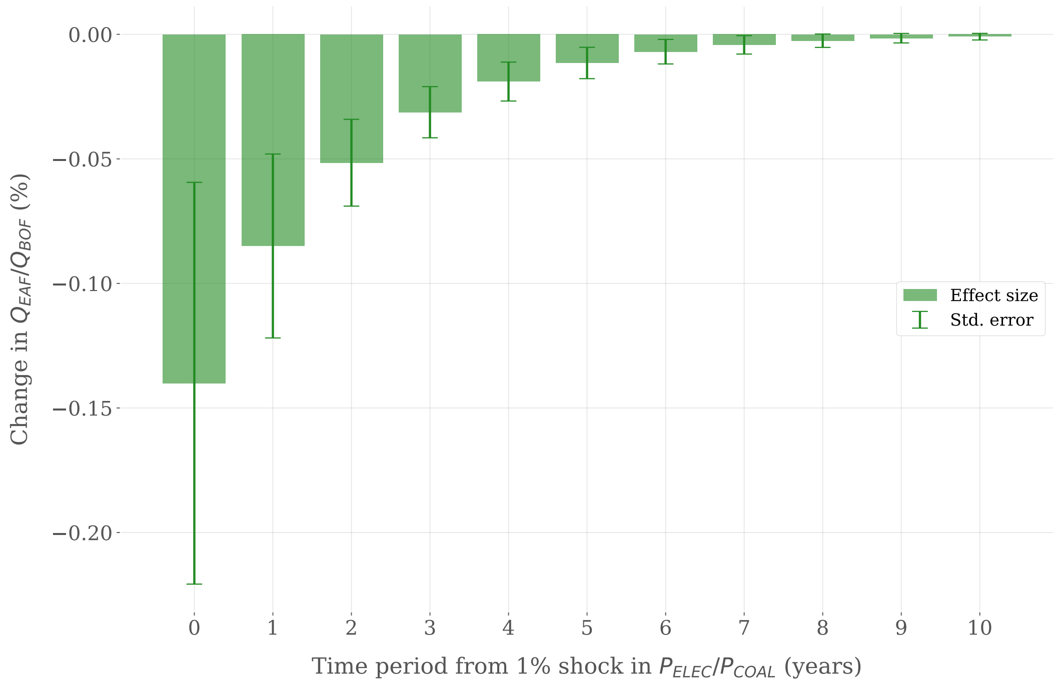

FIGURE 4. *Lag distribution of the partial adjustment model, Equation 4.*

A forecasting application

The European energy market is in turmoil at the time of writing. As such, long-term forecasting of energy prices is an even more perilous exercise than usual. Nevertheless, as we were unable to obtain long-term forecasts for the German producer price index for electricity and the import price index for coal, we modelled the long-term development of P_{ELEC}/P_{COAL} ourselves in order to examine the effects of a simple extrapolation of current trends in energy prices on German steelmaking. An ARIMA(2,1,0) model fitted to the historical development of $\log(P_{ELEC}/P_{COAL})$ was the best ARIMA(p,1,q) model for $p,q \leq 2$ by AIC, and provided a reasonable extrapolation of the current trend in energy prices, along with wide-enough confidence intervals to account for several hypothetical scenarios, as can be seen in Figure 5. The mean forecast for 2050 is $P_{ELEC}/P_{COAL} \approx 75\%$.

Inserting this exogenous forecast into the estimated partial adjustment model, we computed a corresponding forecast and confidence intervals for Q_{EAF}/Q_{BOF}.[6] For ease of comparison with the literature (e.g. Fleiter et al., 2021) we converted the ratio of electric steel to oxygen steel, Q_{EAF}/Q_{BOF}, to the ratio of electric steel to total steel, Q_{EAF}/Q_{Tot}, using Equation 5. Figure 6 shows the results of the

[6]The confidence intervals around Q_{EAF}/Q_{BOF} take into account the confidence intervals around the forecasts of P_{ELEC}/P_{COAL} as well as the standard error of the estimated ARDL coefficients.

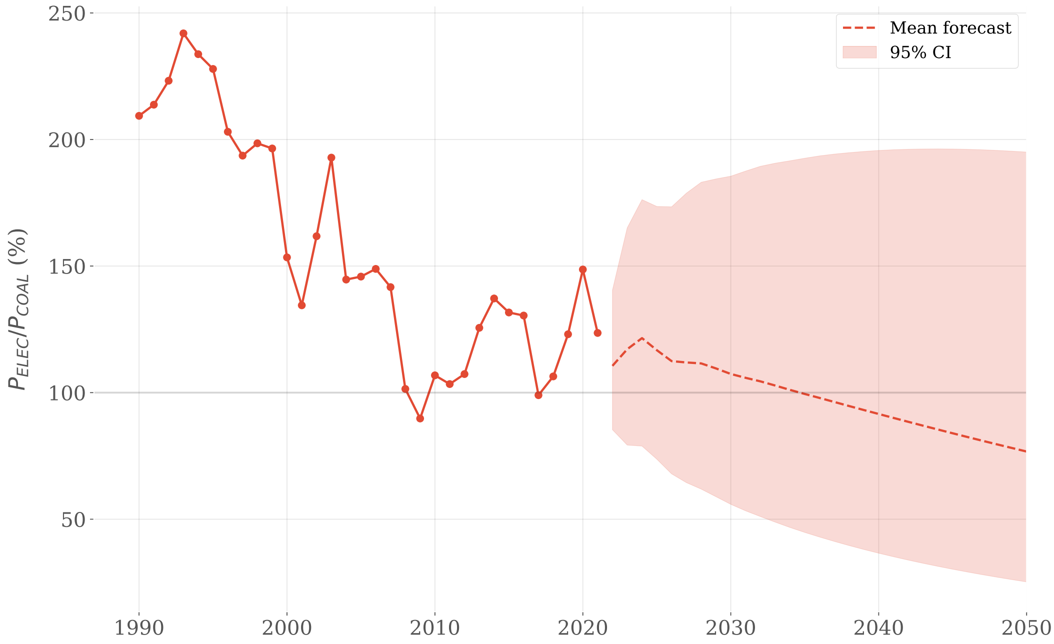

FIGURE 5. *Historical development of P_{ELEC}/P_{COAL} along with the mean forecast and 95%confidence intervals from an ARIMA(2,1,0) model.*

computation.[7] If current trends continue, the mean prediction of the ARDL model is that the share of secondary steel production in Germany via the EAF increases slowly, at a rate of 0.44% per annum, to reach 35.6% of total German steel production in 2050. The development in energy prices significantly influences the long-term uptake of the EAF, with cheap electricity ($P_{ELEC}/P_{COAL} \approx 25\%$ in 2050, cf. Figure 5) boosting the share of secondary steel production to $(43.9 \pm 1.8)\%$ of the total.

4. Discussion

Our analysis demonstrates that technology choice in German steelmaking began to cointegrate with comparative energy prices beginning in the early 90s: an interesting question for future work is to extent to which this has to do with German reunification. The short and long-run effects of energy prices were captured in a partial adjustment model; the ratio of electricity to coal prices was seen to have a sizeable effect on the long-term uptake of the EAF for secondary steelmaking. For the social planner keen on increasing the share of secondary steelmaking, the takeaway in terms of long-term energy policy is clear: the downward trend in the ratio of electricity to coal prices must continue.

[7] The forecast was corrected for bias via a "smearing" back-transformation (Duan, 1983).

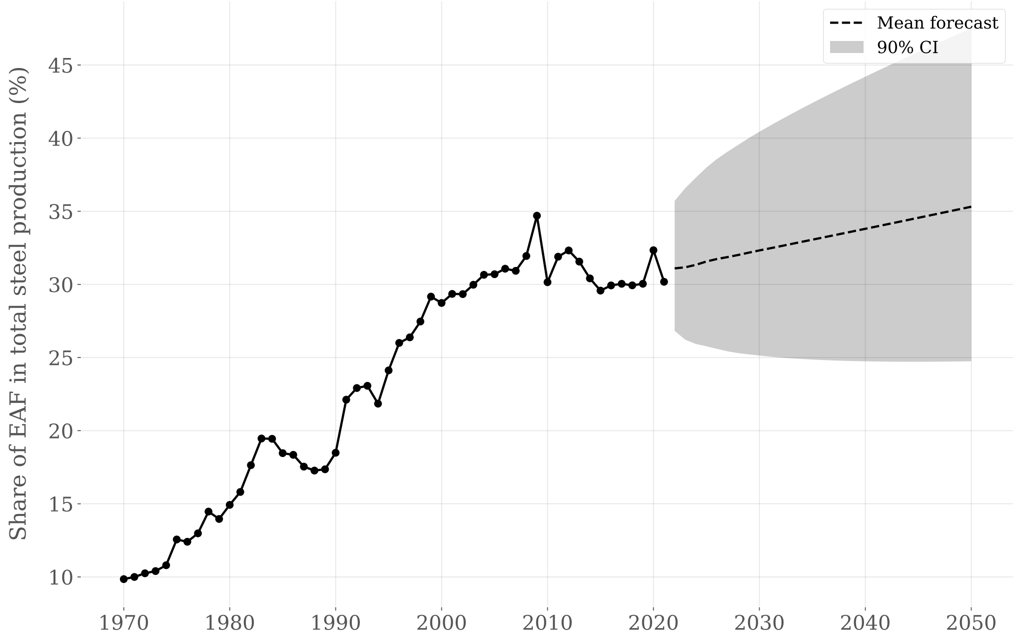

FIGURE 6. *Historical development and mean forecast with 90% confidence intervals for the share of the EAF in total steel production.*

Carbon pricing in tandem with targeted subsidies could be employed to desired effect.

In this article, the price of carbon was integrated into the price of electricity; future work might focus on disentangling this effect, especially as the EU Emissions Trading System matures and more data becomes available. Other prospects for extending the analysis in this paper include the consideration of other factor prices, particularly final products and raw materials, as well as the quantification of the effects of what we termed "unobserved factors", such as international competition, on both factor prices and steel production (cf. Ma, 2021; Vögele et al., 2019; Chalabyan et al., 2018). Cross-country comparisons of the influence of factor prices (cf. Flues et al., 2015) are also likely to be of interest. Finally, Figure 5 reinforces the volatility of energy carrier prices for producers in this sector; future work may focus on examining the effect of factor price volatility on steelmaking technology diffusion, particularly in the long term (cf. de Magalhães Ozorio et al., 2013).

A natural limitation of this study is the inability to infer from historical data the potential of disruptive technologies, such as hydrogen-based direct-reduction for ironmaking, to alter the landscape of primary steelmaking; all our conclusions are concerned with the EAF as employed for secondary steelmaking. Scenarios for EAF deployment in primary steelmaking may be found in other studies such as those of Harpprecht et al. (2022), Fleiter et al. (2021), and Arens et al. (2017). Additionally, our approach focused on comparative shares of steelmaking technology; this is however only a part of the story. In order to obtain the fullest picture of the future of steel production, the total level of production must also be studied, as in the literature just cited. We hope that our results may be combined with these and other studies to generate further insights for the social planner.

Declaration of Interests

The authors declare no competing interests.

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