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DO FIRMS INNOVATE IF THEY CAN RELOCATE? EVIDENCE FROM THE STEEL INDUSTRY

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Do Firms Innovate if They Can Relocate?

Evidence from the Steel Industry

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Abstract:

We estimate the effect of coal prices on steel plant location worldwide and production preferences for BOF, a polluting technology, and EAF, a greener one. A 1% increase in national coal prices could reduce the share of BOF and EAF units of that country over total active steel-making units present in the world by around 0.61% and 0.43% respectively. We simulate the implementation of a stringent European carbon market and find a non-negligible shift in steel production outside Europe, with limited impact on the technologies employed to produce steel. If applied worldwide, the same policy would strongly affect production in Asia, which relies on BOF and currently benefits from lower coal prices.

Keywords: Steel industry; firm relocation; technological change; energy prices.

JEL Classification: O14, O33, Q41, Q42

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1. Introduction

The Paris Agreement (2015) has set the ambitious objective of limiting global warming below 2°C. However, while economists have long argued that the most effective policy to achieve this would be either a global price of carbon or a global carbon market (e.g. Stoft et al., 2013; Weitzman, 2014), extensive international discussions have so far not been successful in delivering it.[1] To date, only a small number of independent carbon schemes are operative (e.g. the EU, Japan, China and California). In all these schemes, the price of carbon is far below its social cost as estimated by integrated impact assessment models.[2] One of the main reasons why carbon prices are low on these markets comes from the risk that regulated industries lose competitiveness. For sectors that are both energy intensive and largely exposed to international competition, unilaterally implementing a carbon tax or trading scheme may push industries to relocate.

In this paper, we estimate the effect of changes in coal prices on steel plant location worldwide. We simultaneously observe changes in production choices. More precisely, we can track whether steel plants start relying or not on recycling processes which are known to be far less energy intensive. Looking jointly at the effect of energy price shocks on plant location and production preferences constitutes the main contribution of this paper.

A large body of economic literature has looked at the effect of energy prices or environmental regulation on firm performance and location. Earlier studies attempting to measure the effect of environmental regulation on net exports, overall trade flows, job creation or plant-location decisions produced estimates that were either small or statistically insignificant (Jeppesen et al., 2002; Morgenstern et al., 2002; Jaffe et al., 1995). Ever since, studies focusing on US-based pollution-intensive industries have shown that environmental regulation tended to decrease

[1] Leading emitters (e.g., US, China, India) diverge on the concept of “differentiated responsibilities” as proposed initially in the Berlin Mandate of 1995. While the developing countries argue that severe emission caps may hinder the economic growth trajectory of such countries, developed nations, mainly the United States, argue that having differentiated targets defeats the purpose of a common market, as global pollution levels would continue to grow as usual through the pathway of leakage.(Bosetti et al., 2014).

[2] Nordhaus (2017) estimates that the social cost of carbon is around \$31/tCO_2 eq. for the current period. Yet, in 2015, the traded price of carbon ranged from \$1 to \$13/tCO_2 eq. worldwide, and 90% of carbon permits were traded at less than \$10/tCO_2 eq. (WBG and ECOFYS, 2015). In the EU, the carbon price oscillated between \$3 and \$10/tCO_2 eq. between 2013 and 2015 (Marcu, 2016).

output and profits (Aldy and Pizer, 2015b; Ho et al., 2008; List et al., 2003; Greenstone, 2002). Regulated and polluting industries would also experience a reduction in exports and an increase in imports, in particular if they are geographically mobile (Aldy and Pizer, 2015a; Levinson and Taylor, 2008; Ederington et al., 2005). Therefore, the location of plants seems impacted by environmental regulation and/or energy prices. Using longitudinal data on outward FDI flow of German manufacturing industries, Wagner and Timmins (2009) find evidence of a pollution haven effect in the chemical industry. For the US, Kellenberg (2009) finds that US multinationals' subsidiaries in foreign countries exploit less stringent environmental regulation. It attributes 8.6% of the growth of these subsidiaries to the falling levels of environmental regulation in destination countries. Kahn and Mansur (2013) use county-level US data and observe that energy-intensive industries concentrate in low electricity price counties, while labor-intensive industries avoid pro-union counties. They also find mixed evidence that pollution-intensive industries may locate in counties featuring relatively lax Clean Air Act regulation. In parallel, the existence of locational effects may encourage neighboring States or countries to adapt their regulations to the ones of their neighbors (Fredriksson and Millimet, 2002). Some recent papers study the impact of the EU-ETS on firm relocation (Dechezlepretre et al., 2014, Borghesi et al., 2016, Koch and Basse Mama, 2016). Both Borghesi et al. (2016) and Koch and Basse Mama (2016) find evidences of relocation caused by the EU-ETS particularly for these sector exposed to international competition. On the other hand, Dechezlepretre et al. (2014) find no evidence of carbon leakages triggered by the introduction of the carbon scheme. A limitation of their study is that they focus only on the initial period of activity of the EU-ETS, up to 2009, and they do not rule out the possibility of finding different results in case of an increase of the policy stringency by the EU policy makers. The studies focusing on the impact of environmental regulation (or energy taxation) on firm performance and location paid little attention to the concomitant effect of environmental stringency on technology development and diffusion. Evidence that energy prices foster the adoption of cleaner technologies has been found in very diverse industry contexts (e.g. Cohen et al., forthcoming; Aghion et al., 2016; Dechezlepretre et al., 2011; Popp, 2006; Brunnermeier and Cohen, 2003; Popp, 2002; Newell et al., 1999; Jaffe and Palmer, 1997; Lanjouw and Mody, 1996). Yet, none of the above-mentioned studies considered plant location and technological choice as simultaneous decisions. The two are likely to interact.

Even though changes of location may be encouraged by the availability low environmental standards in some countries, the choice to relocation will be ultimately dependent on the cost of compliance, which depends on the availability of low-pollution technologies or the potential for their development.

This paper dives into this topic while focusing on the steel industry. This sector is particularly relevant to assess the role of energy taxation in climate change mitigation. Steel is one of the most energy intensive industries and a very large emitter of greenhouse gases: it represents 27% of all greenhouse gas emissions (GHG) from industry worldwide (IEA, 2017).[3]

We directly estimate the impact of an increase in coal price expectations on the share of steel producing units located in a country relative to all active steel-making units in the world in that year, separately evaluating this figure according to the technology they use to produce steel.[4] We use steel plant data (1960-2014) collected by the OECD and covering 132 countries. The dataset records the opening, operating and closing times of steel plants, along with the main technology that they employ to produce steel. Currently, two major steel-making technologies are available. The Basic Oxygen Furnace (BOF) is highly energy intensive and polluting whereas the Electric Arc Furnace (EAF) is a recycling technology able to cut up to a quarter of the emissions from the production process. The OECD data displays if a plant resorts to BOF and/or EAF, allowing us to

[3] In 1990, steel industry's global energy consumption was estimated to be 18 to 19 Ej, accounting for 10 to 15% of the annual global industrial energy consumption. By 1995, its CO2-emissions were estimated at 1442 Mt, or about 7% of global anthropogenic CO2-emissions (IEA, 2016). In more recent years, as a consequence of the rapid growth in the Asia Pacific region, steel production has shifted: Asia now produces over 60% of global output (in particular, China accounts for almost 50% of crude steel production in 2015); in contrast, the EU-28 and NAFTA regions share of global production has decreased from 28% in 2005 to 17% in 2015 (WSA, 2016). Additionally, there has been a steady increase of BOF production in emerging economies (above all China, but also India and Brazil), where raw materials are cheap and steel scrap is not yet adequately available; while north-western countries, which are overall more concerned about environmental preservation, closed up their BOF plants much faster than their EAF ones.

[4] In the steel sector, a few studies have looked at the impact of energy prices on firm production choices. However, they do not properly address the endogeneity caused by the simultaneous determination of production choices and input prices. Reppelin-Hill (1999) finds no response of the share of EAF over total steel production to change in input prices: namely coal, iron ore, scrap and electricity. She looks at 30 steel producing countries for the period (1970-1994). Other more recent and more geographically restricted studies find significant negative elasticities between the price of coal and dirty steel production. Schleich (2007) show that, for the case of German steel-makers, an increase in 10% in the relative price of coal to steel reduces fuel consumption in BOF by 0.1%, by increasing the use of EAF for overall production of steel. Flues et al. (2015) consider in the analysis Germany, Italy, Spain, France and the UK; they find that an increase by 1% in the price of coal leads to a decrease of 0.12%-0.14% in energy consumption for steel production. Mathiesen and Maestad (2004) aims to jointly account for the locational and technological choices of manufacturers in a static numerical partial equilibrium model of the world steel industry. These authors however rely on expert opinion to assess the magnitude of the elasticities relevant to their modelling exercise, in particular the elasticity of steel production technologies to changes in energy prices.

produce country aggregates by technology. We match the OECD data on steel plants with coal price statistics from the International Energy Agency and, for China, information from the Chinese Ministry of Coal and the Bohai-Rim Price Index. The coal data covers 22 countries for the period 1978-2014. Hence, our final dataset comprises 22 countries for which we could match coal prices with steel plant data over 37 years. These 22 countries encompass around 82% of the steel produced worldwide.[5]

We find that an increase in coal prices at national level have a negative effect on the size of steel manufacturing in a country. In our preferred specification, a 1% increase in coal prices reduces the share of BOF units in that country, compared to the rest of the world, by around 0.61% and the share of EAF units by around 0.43%. This consistently suggests that the most energy-intensive types of units are more affected by increases in coal prices.

To assess the impact of coal prices on relocation, we simulate the impact of the implementation of a global carbon market on the location of steel plants for the 22 countries that we cover. In the carbon market, we set the price of GHG emissions at \$31/tCO_2 eq. This is the estimate of the current social cost of carbon in Nordhaus (2017). We assess the impact of two different scenarios and compare them to a business-as-usual scenario: a) all countries join a global carbon market; b) European countries only increase the stringency of the EU ETS, increasing the price of GHG emissions by \$31/tCO_2 eq. for the steel industry. Our econometric estimates allow us to determine the share of BOF and EAF plants remaining in each country depending on the geographical amplitude of the carbon market. In these two scenarios, we find that the increase in the price of coal has a positive impact on the final share of active EAF units over the share of total active units in a region. In the scenario in which only European countries implement the carbon scheme, we observe a non-negligible shift in production (1.65 percentage points) from the countries that are part of the carbon market to the non-participating countries. An important finding is that we also observe a shift in production in the case where a carbon market is applied worldwide, this time from Asian countries to other regions of the world. This shift of 9.74 percentage points is much larger than for the unilateral carbon scheme in Europe. Historically, Asian firms have benefitted from lower coal prices and currently rely more on BOF technologies

[5] This figure is obtained from the estimates given by the World Steel Association for the year 2014.

(as reported in the data section, cf. Figure 1 and Table 1). Therefore, when the global carbon tax is implemented, Asian firms are more affected than European and North American ones.

These effects, found in the case of steel manufacturing, may apply to other highly energy intensive industries that are also strongly exposed to international competition, such as the cement industry or the chemical industry. They have strong policy relevance. They may largely explain the reticence of EU countries to increase the stringency of the EU ETS, or to allow for exemptions in the steel sector due to the risk of carbon leakage. National industrial interests are one of the main reasons why multinational carbon markets are not being put forward. Since countries will be asymmetrically affected by it, systems with quota allocations that take into account the current distribution of firms across countries may be necessary if a multilateral agreement on a common carbon market is to be found.

All these results have been obtained from an econometric setting that circumvents several difficulties. First, our econometric strategy accounts for the fact that building and operating a steel plant requires making long-term investments. It follows that investors should be forward looking and care more about the expected price of coal in the coming years than about its current market price. We compute national average coal price expectations with autoregressive integrated moving average models (ARIMA) to produce expectations about future coal prices that take into account basic knowledge (by manufacturers) of previous energy price trends. Second, the steel industry is the largest buyer of coal. Therefore, the price of coal is endogenous since it depends on the size of the steel sector. We circumvent this problem while relying on the lags of coal prices as instruments in a setting that tolerates the use of pre-determined variables as instruments. More precisely, we use the pre-sample mean estimator exposed in Blundell et al. (2002). The general idea is to inject additional information into the econometric model in cases where pre-sample data is available for the dependent variable. In this case, we use the pre-sample data for 1960-1981 on the average amount of steel-producing units in country *i*. Blundell et al. (2002) prove that this strategy is both more efficient and less biased than traditionally used first differenced estimators, even for a small amount of observations and pre-sample periods. Furthermore, the estimator by Blundell et al. (2002) is a non-linear count model that restricts predicted outcomes to be strictly positive or equal to zero. This type of models offers a much better account that any linear model of the situations where we observe no steel plant of technology s in country i operating at time t. Our results are furthermore robust to several changes in the base specification, in particular regarding the calibration of the estimation method and the computation of expected coal prices.

The rest of the paper is structured as follows. Section 2 presents the data while providing a brief overview of the steel industry. Section 3 presents our estimation technique. Section 4 comments on the results and the main robustness checks performed. Section 5 presents our simulation exercise and section 6 concludes.

2. Data

This piece of research relies on OECD data on steel plant location and data on coal prices at national level. We briefly describe both data sources hereafter.

2.1 OECD data on the steel industry

The steel plant data has been assembled by the OECD and provides information on the location of steel plants in 132 countries. For some countries, data is available since the beginning of the 20th century whereas it starts by around 1960 for most of them. The most disaggregated layer of observation in the database is the production unit: a steel plant is composed of several units, which may become operative or close down at different moments in time, even if they are on the same site. The data records the opening and closing year of these different units. Finally, units may also use different production technologies. The dataset records whether a unit is EAF or BOF.

A limitation of this study is that we don't have information on the intensive margin, i.e. production capacity, of the steel plants under analysis. It is likely that many of these plants would stay open for a long time, but they will operate at reduced capacity in times of high coal prices. All throughout the analysis, we assume that production capacity remains stable across the years. In addition, EAF units are on average smaller than BOF ones. This does not jeopardize our results, but it actually reinforces them. The emissions decrease, entailed by a reduction in BOF units and an increase in EAF ones, will be even bigger than what anticipated in this paper where EAF and BOF are assumed to have the same production capacity.

BOF is a technology that came into wide adoption in the 1960s.[6] It takes, as inputs, iron ore and coking coal, and produces steel in two integrated steps. In the first step, coal is heated up to 2400 degree Fahrenheit, and transformed into coke. Coke is then combined with iron ore to produce molten iron. In the second step, molten iron and some scrap are transformed into steel in the basic oxygen furnace. CO_2 is emitted through both the raw material and the combustion process. Furthermore, CO_2 can be emitted indirectly through the use of electricity, usually generated with on-side coal-fired power generators. For BOF, the blast furnace and other combustion processes contribute 88% of CO2 emission, while indirect electricity consumption contributes 12% (EPA, 2012; OECD, 2013; IEA, 2012).[7]

EAF is a different steel-making process which uses ferrous scrap as main input instead of raw materials (Giarratani et al., 2013). Additionally, it makes use of electricity to convert scrap into new steel. The electricity produced to run EAF units is usually generated on site using steam coal. The first EAF plant was established in the US in 1907 but, initially, the quality of the steel produced was lower than the one obtained through BOF and not enough scrap was around to make it cheaper to produce only through recycling.[8] At the beginning of the 20th century, it was difficult to control the quality of the scrap, therefore, EAF steel was considered a byproduct. With technology advancement there has been improvements in the quality of steel produced via EAF and in the second half of the 20th century it started to spread as an almost-perfect substitute to BOF. The main source of emissions in the EAF process is through electricity usage, which accounts for about 50% of emissions (EPA, 2012). As EAF uses recycled ferrous scrap, and bypasses the coke production process, it is considered a more advanced technology with less energy burden. However, the fact that EAF resorts to scrap implies that EAF could not possibly

[6] In the 19th century and early 20[th] century, the steel-making process widely used was Open Heart Furnace (OHF). It employs as main inputs raw materials such as iron ore, natural gas, oil or coal. It is a slow and inefficient procedure which, from the 1960s, has been completely replaced by the more efficient Blast Oxygen Furnace (BOF), which uses the same inputs, but exhibits big improvements in efficiency: approximately 1 BOF is required to replace 6 OHFs. Given this phase-out we exclude OHF from the analysis.

[7] BOF can use scrap to produce steel, but up to a maximum of 25% of the amount of total inputs.

[8] Steel scrap can have different sources: “home scrap” generated within the plant (nowadays it is not sufficient any more to produce steel due to the requirement of very high volumes of materials, therefore it needs to be integrated with the one purchased outside the firm); “new/prompt scrap” which is produced within the industrial activity of other firms (it is the same as home scrap, but it is not produced within the firm); “post-consumer scrap” which returns in the market after it ends its useful life (it could be very quick, as for cans, but it could take up to some years, as in the case of cars) (Yellishetty et al., 2011).

fully substitute to BOF. The diffusion of these two steel-making technologies crucially depends on the availability of input materials. In general, EAF is more frequent in (developed) countries where scrap is sufficiently available to sustain the production.

Table 1 below provides information on the number of steel units recorded in the data for three periods (1982-1990, 1991-2000, 2001-2014)[9], with a breakdown by technology and geographical location. It only displays the data used in the econometric estimation, i.e. the one that could be matched with coal price data and covers 22 countries. More complete descriptive statistics for unmatched countries and data for before 1982 are available in Appendix A.

Also, please note that EAF plants have typically a smaller capacity than BOF. On average, one BOF unit produces the same amount of steel as almost 3 EAF units (OECD, 2015). Unfortunately, our data does not feature the production capacity of each unit or plant.

Table 1: Descriptive statistics of OECD data on steel plant location and main technology used in production (1982-2014)

Period	1982-1990		1991-2000		2001-2014	
Technology	BOF	EAF	BOF	EAF	BOF	EAF
North America	70.3	234.8	64.8	210.0	54.3	183.3
Europe	113.3	180.9	100.6	161.6	84.3	166.7
Asia	222.1	217.9	255.4	285.7	339.7	345.9
Other	9.0	5.4	8.8	7.0	7.0	7.0
Total	**414.8**	**639.0**	**429.6**	**664.3**	**485.3**	**702.86**

Notes: The table reports the average number of active units of steel-making production in each region of the world over three different time periods. Note that we only report figures for the restricted list of 22 countries used in the regressions hereafter. North America includes Canada and the US; Europe includes Germany, Turkey, Spain, Italy, France, Poland, Belgium, Czech Republic, Sweden, Finland, the Netherlands, Portugal, Switzerland and Norway; Asia includes China, Japan, Russia and India; Other includes Australia and Chile.

In terms of GHG emissions, EAF units emit, for the same amount of steel produced, 4 times less than their BOF counterparts (OECD, 2013 IEA, 2012). This is why, in the remaining of the analysis, EAF is considered as a greener alternative to BOF. However, switching from BOF to EAF is not the only choice available to manufacturers if they want to reduce GHG emissions. Worrel et. Al. (1999) discusses in details many alternative measures to improve the energy efficiency of steel manufacturing (e.g. preventative maintenance, cogeneration, heat recovery,

[9] Coal prices are available starting from 1978, but, since in the final estimation we will use the expected prices of coal instead of the actual ones and given that we need at least 4 years to estimate the forecast, our analysis will cover the interval (1982-2014).

etc). Nevertheless, technology switching remains the one of greater impact on the emissions performance of a plant. In this study, we have no data on the efficiency of active EAF and BOF units and, therefore, cannot evaluate the extent to which an increase in coal prices may lead to changes in the efficiency of installed EAF and BOF units.

2.2 Coal price data

We use the industrial coal price[10] data from the International Energy Agency (IEA), converted to constant 2010 USD,[11] except for China, for which we use the data from the Chinese Ministry of Coal, integrated with the Bohai-Rim Price Index. These sources report both coking coal and steam coal prices starting from 1978.

Steam coal, or thermal coal, is used primarily in electricity generation, while coking coal, or metallurgical coal, is used in steel-making. In BOF processes, coking coal is converted to coke by eliminating virtually all impurities and leaving close to pure carbon. This process involves heating coking coal in coke ovens to around 1000 to 1100 degrees Celsius in the absence of oxygen. The coking process takes 12 to 36 hours in the coke oven, and the finished coke is cooled before transferring to blast furnaces and combined with iron ore to make molten iron. Around 600kg of coke produces 1000kg of steel, which mean around 770kg of coking coal is used to produce 1000kg of steel (WCA, 2017) The EAF processes do not involve mixing coke with iron-one. However, they are reliant on electricity generated by coal-fired power plants. With EAF, around 150kg of steam coal is used to produce 1000kg of steel (WCA, 2017).

Coking coal and steam coal prices strongly correlate (Pearson correlation coefficient is 0.58). Even though EAF uses steam coal and BOF coking coal, we only include coking coal prices as an independent variable in our preferred model. This allows reducing losses of precision due to multicollinearity. Nonetheless, this choice implies that the price of coal is measured with error for EAF units. We solve this problem econometrically since we will be instrumenting for coal prices.

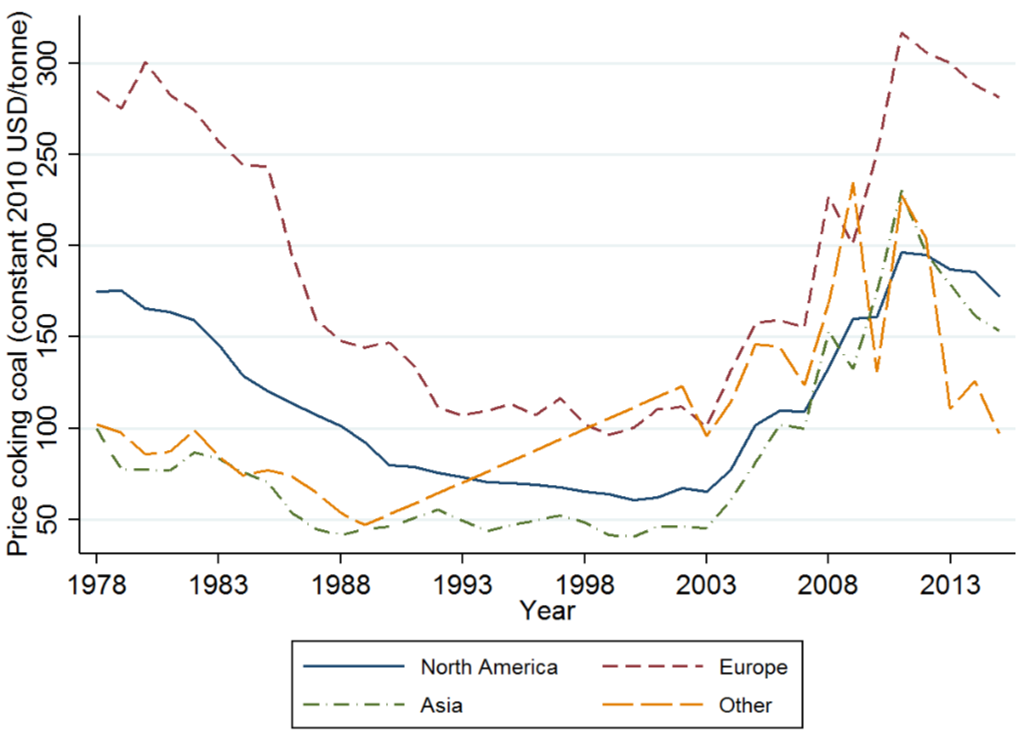
[10] We collected the total price charged to the industrial sector.

[11] Coal prices are initially extracted in national currency/tonne. To convert them in constant 2010 USD/tonne, we apply the formula: $P^{cons2010} = \frac{P_t^{LC}}{deflator_t^{GDP}} \frac{deflator_{2010}^{GDP}}{r_{2010}^{x}}$, where $P^{cons2010}$ is the price of coal expressed in constant 2010 USD/tonne, P_t^{LC} is the price of coal expressed in local currency/tonne at time t, $deflator_t^{GDP}$ is the GDP deflator for that country at time t, $deflator_{2010}^{GDP}$ is the GDP deflator of that country in 2010, and r_{2010}^{x} is the exchange rate between the local currency and USD in 2010.

Furthermore, in Appendix C4, we use steam coal prices and not coking coal in alternative regressions, and both steam and coking coal prices in appendix C5. Results with these alternative specifications are consistent with the ones obtained in our preferred specification.

Figure 1 presents the evolution of average coking coal prices in North America, Europe, Asia and the other regions of the world for 1978-2014. Coking coal prices observed a strong decline in all regions in 1988 because of the concomitant oil price collapse (King and Tang, 1988). After 2000, they then abruptly increased because of the so-called commodities super-cycle, mainly due to the rising demand from emerging markets such as the BRIC countries (Schwartz and Creswell, 2015). On the other side, coking coal prices have been consistently lower in Asia compared to Europe or North America.

Figure 1: Evolution of coking coal prices in major geographical areas (1978-2014)



Notes: North America includes Canada and the US; Europe includes Germany, Turkey, Spain, Italy, France, Poland, Belgium, Czech Republic, Sweden, Finland, the Netherlands, Portugal, Switzerland and Norway; Asia includes China, Japan, Russia and India; Other includes Australia and Chile. Average prices are unweighted (i.e. they do not take into account the relative size of each country).

3. Empirical method

We develop an empirical strategy that allows estimating the impact of expected coal prices on the size of steel manufacturing in a country. Our general approach consists in applying a count model with the share N of steel units using technology $s \in \{BOF; EAF\}$ in country i during year t over the total number of active units in the world in that year as the main dependent variable. In this national-level count model, we have separated the counts of BOF and EAF units since this provides us with the right level of aggregation to simultaneously look at cross-country relocation and technological choice.[12]

The expected price of coal, denoted $p_{i,t}^{*}$, constitutes the independent variable of interest of our model. We aim to estimate a model such that:

$$N_{s,i,t} = f(p_{i,t}^{*})$$

To estimate such a model, we are confronted with two difficulties. The first difficulty is that we do not observe the expected price of coal in country *i* at time *t*, but its actual realization, which we denote $p_{i,t}$. However, the right variable of interest is the expected price of coal because manufacturing companies are likely not to base their production decision on current inputs' prices. They will rather take in consideration their expected value in the future. This is particularly true for a sector like the steel one because investments are costly and have a long lifetime.

The second difficulty is that expected coal prices constitute an endogenous variable. The total demand for coal in country *i* and at time *t* depends on the demand for coal from the steel industry. Since the price of coal in country *i* and at time *t* depends on the demand for coal in this same country, it mechanically depends on the demand for coal from the steel industry. Therefore, the total number of steel plants using technology *s* in country *i* and at time *t* is a determinant of the price of coal in country i at time t. Since $N_{s,i,t}$ has an impact on $p_{i,t}$ while it also depends on $p_{i,t}$, these two factors are simultaneously determined. On the other hand, expectations about future coal prices necessarily depend on the current price of coal. It follows that $N_{s,i,t}$ and $p_{i,t}^{*}$ are also simultaneously determined.

We resolve these two problems as follows.

[12] Under specific conditions, count models applied on aggregate data are furthermore equivalent to binary choice models applied at more disaggregate levels (Guimaraes et al., 2003).

3.1 Computing expected coal prices

To compute expected coal prices, we consider that a perfectly rational agent forecasts future prices based on the information that s/he has. We assume that past prices constitute all the information easily available to economic agents, such that their expectations about future prices are a function of past prices. In this framework, expectations can be recovered with a time-series model that produces a forecast of the coal price at time t+1, t+2, t+3, etc. with the coal price at time t, t-1, t-2, etc. In practice, we recursively apply autoregressive integrated moving-average models (ARIMA) on national annual time-series of real coal prices. The ARIMA model that we use to make the predictions is a first-order autoregressive model. This is because this model proved to be the best fit to the data:

$$p_{i,t} = \mu_i + \gamma_i p_{i,t-1} + \varepsilon_{i,t}$$

In this model, the price of coal in each country i is regressed on its first lag. $\varepsilon_{i,t}$ is a term of error and μ_i and γ_i are parameters to be estimated. For each period t and country i, the ARIMA model is estimated with data from the previous 10 years. When we lack information on the previous 10 years, we estimate the model with all available years, provided that we have data for the previous 4 years at least. In each case, we then take the 10-year average of forecasted prices (for time t+1, t+2, t+3, etc.) as our value for the expected coal price, $p^*_{i,t}$. Therefore, the ARIMA model is re-estimated for each time period t present in the sample, except for the first four years of our data (1978-1981), for which we did not have enough data to run the ARIMA model, i.e. ($t \in [1982; 2014]$). We then make out of sample predictions and, year after year, we allow steel companies to update their beliefs about future prices as soon as new information is available. Detailed statistics on the output of the ARIMA model and the predictions obtained are reported in Appendix B.

Furthermore, we performed several robustness checks to make sure that our final results are not dependent on the choices made to compute energy price expectations. All robustness checks relative to the choice of the coal price variable are reported in Appendix C. They are also briefly discussed in the results section.

3.2 Endogeneity of expected coal prices

Our econometric strategy needs to deal with the endogeneity of the expected price of coal. In the literature, the most frequently suggested technique consists in using cost shifters as instruments, i.e. factors that are correlated with the cost of producing coal, and not with the demand for coal (e.g. Berry, 1994). However, the context of coal and steel production makes it hard to find strictly exogenous instruments: the two sectors are closely related. For example, steel production uses another output of the mining industry as an input, namely iron ore. Therefore, supply shocks on the extraction of coal may also affect the extraction of iron. If cost shifters cannot be used as instruments, an alternative would consist in using shocks on the demand for coal that are not correlated with the demand from the steel industry as instruments. This approach is the one of Hausman et al. (1994), who instruments the price of a product in a given market j, with the price of this same product on other markets. Provided that demand shocks are not correlated across markets, this instrumentation strategy is valid. Yet, the steel industry is the main demander for coal and markets are integrated across regions. When not used to make steel, coal is used to produce electricity. The assumption that shocks on the electric market are not correlated with the steel market is not serious. For example, steel is used in construction, and shocks on the construction sector should translate into a simultaneous increase in energy demand and the demand for steel.

We adopt a conservative approach and consider that most of the (demand and supply) shocks on coal prices are likely to be correlated with contemporaneous shocks on the steel industry. As a consequence, we abstain from using fixed effect models since they rely on the assumption of strict exogeneity of the instruments. To relax the assumption of strict exogeneity of the instruments, applied economists have usually relied on models in first differences (Roodman, 2008). These models present the advantage of allowing for pre-determined variables to serve as instruments, for example the lags of both the exogenous and endogenous variables. However, these models lack efficiency, in particular when time-persistent processes are studied. Models in first differences are also subject to small sample bias. With a total sample of around 900 observations and an industry that relies on long-term investments, first difference models are likely to provide inefficient estimates, if not inconsistent, in the present case.

In such an econometric context, Blundell, Griffith and Windmeijer (2002) recommend using pre-sample mean estimators. A specific interval of time $\{t_1;\, t_f\}$ is set to be the time of the analysis. In this interval, the set of information about dependent and independent variables is complete. There is, additionally, a pre-sample interval $\{t_i;\, t_0\}$ where only information on the dependent variable is available. A mean of the dependent variable is estimated over $\{t_i;\, t_0\}$ and included as a control variable in the estimation. With small samples, Blundell, Griffith and Windmeijer (2002) show that pre-sample mean estimators are more efficient and significantly less biased than first difference estimators, even when time persistence is not extreme and for a small number of pre-sample observations. The intuition why pre-sample mean estimators are superior to first difference estimators is quite simple: they incorporate additional information into the model, namely the pre-sample mean of the dependent variable. The main limitation explaining why these estimates are barely used is that they can only be applied if pre-sample information on the dependent variable is available to the econometrician.

In the present case, we have data on $N_{s,i,t}$ since the 1960s, while our data on $p^*_{i,t}$ starts in 1982. We have 22 years of pre-sample information on $N_{s,i,t}$ which can be used to run pre-sample mean estimators in the fashion of Blundell, Griffith and Windmeijer (2002).[13] We estimate the following count model:

$$N_{s,i,t} = exp\left(\alpha + \beta \ln\left(p^*_{i,t}\right) + \sigma \ln\left(\bar{N}_{s,i,t_i}\right) + \theta t\right) + e_{s,i,t} \qquad (1)$$

Where $\bar{N}_{s,i,t_i}$ is the pre-sample mean of $N_{s,i,t}$ over $\{1960;\, 1981\}$ and $e_{s,i,t}$ is the error term. α, β, σ and θ are parameters to be estimated. The expression θt captures the effect of time on $N_{s,i,t}$.[14] This expression can be estimated using GMM. To instrument for $\ln\left(p^*_{i,t}\right)$, the lags of $\ln\left(p^*_{i,t}\right)$ are valid instruments provided that contemporaneous shocks on $p^*_{i,t}$ are not correlated with previous shocks. The latter means that shifts in expectation between time *t* and *t-1* arise from the inclusion of new information about $p^*_{i,t}$. This is the case if expectations are rationally formed, or if they follow a random walk.

In our base specification, we simply use $\ln\left(p^*_{i,t-1}\right)$ to instrument for $\ln\left(p^*_{i,t}\right)$. In an alternative

[13] In Appendix D.1, we modify the pre-sample period used for estimation to 1970-1981instead of 1960-1981. Results are similar to our preferred specifications.
[14] Specifications with time-fixed effects where not converging in the non-linear case. We, however, use time fixed effects in a linear version of this specification in Appendix D.2.

specification, we expand the number of lags used as instruments, and run the model with the first five lags of $\ln\left(p_{i,t}^{*}\right)$ as instruments. This allows us to run an over-identification test and make sure that all lags provide the same results when used as instruments. This test corroborates our assumption that there is no correlation between $p_{i,t-1}^{*}$ and $p_{i,t}^{*}$ creating endogeneity. This specification is described in the results section. Finally, we report the results obtained with a fixed effect model with no treatment of endogeneity in Appendix D.3 and the results obtained with a first difference estimator in Appendix D.4. Unsurprisingly, the results of the fixed effect model are inconsistent. The results with the first difference estimator are inefficient. They should also suffer from a small sample bias (Staiger and Stock, 1997; and Blundell and Bond, 1998). The bias of the first difference estimator leads the estimates to be similar to the ones provided by a first differenced model where the expected price of coal would be treated as be exogenous. We also provide the results of such a model in Appendix D.4.

4. Results

Table 2 presents the results of the estimation of equation 1. Column 1 reports the results for the full sample, column 2 for BOF units only and column 3 for EAF units only. For each of these specifications, the pre-sample period used for the estimation is 1960-1981. It is the largest pre-sample interval available to us for all 22 countries. The logarithm of expected coal prices is instrumented with its one-year lag.

Overall, we find that a 1% increase in the expected price of coal in country *i* would cause a decrease in the share of active units in this country, compared to the rest of the world, by around 0.51%. If we look at EAF and BOF separately, the impact of an increase in coal prices appears to be 45% larger for BOF units. It corresponds to a 0.61% reduction for a 1% coal price increase, versus a 0.43% reduction for EAF units. Nonetheless, we cannot conclude that these effects are statistically different from each other.

Table 2: Estimation of the impact of expected coal prices on the share of steel units using the pre-sample mean estimator (Blundell, Griffith and Windmeijer, 2002)

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	BOF (2)	EAF (3)
log. expected coking coal price	-0.507***	-0.607***	-0.433***
	(0.121)	(0.128)	(0.125)
log. pre-sample mean (1960-1981)	0.710***	0.734***	0.672***
	(0.039)	(0.072)	(0.043)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of the logarithm of expected coal price is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

The results displayed in Table 2 rely on the validity of our instrumentation strategy. In particular, we assume that past shocks on expected coal prices do not correlate with the error term ($e_{s,i,t}$), and only determine the value of expected coal prices at time *t*. In mathematical terms, our instrument is valid if $\ln(p^*_{i,t}) = \delta \ln(p^*_{i,t-1}) + v_{i,t}$, with $corr(v_{i,t}, v_{i,t-1}) = 0$. The pre-sample mean estimator tolerates that $v_{i,t}$ is correlated with $e_{i,t-x}$ with $x \geq 1$, whereas a fixed effect model would require $corr(v_{i,t}, e_{i,t-z}) = 0$ with $z \geq 0$.

We corroborate that this is the case in the present situation. We jointly use the first five lags of $p^*_{i,t}$ as instruments in Table 3. The general idea of this process is that deeper lags are even less likely to be correlated with $e_{s,i,t}$ than the first lag. If the first lag is not an exogenous instrument, then it should be providing different estimates than the ones obtained with deeper lags. Using up to 5 lags, we can apply this same logic to the 2nd lag, the 3rd lag and so on, assuming that, at least, shocks on the 5th lag of expected coal prices should not be correlated with $e_{s,i,t}$. The sufficient condition for the 5th lag to be a valid instrument is that $corr(v_{i,t}, v_{i,t-5}) = 0$. All in all, results in Table 3 are very close to the ones obtained with only one lag. Furthermore, we can run an over-identification test since we have more instruments than variable. We reject the hypothesis that at least one instrument would give results different than the other instruments.

The results of Tables 2 and 3 are robust to many specification changes. In particular, results are not altered when we directly use expected coal prices instead of their logarithm in the model (see Appendix C.1). Furthermore, we used a specific technique to produce coal price expectations. However, our general results do not rely on the way expectations were computed. We obtain similar results when we use contemporaneous prices ($p_{i,t}$) instead of expected prices ($p^*_{i,t}$) as the main independent variable (see Appendix C.2). To allow for more flexibility, we also try using distributed lags for coal prices as independent variables in an alternative specification (see Appendix C.3). Results lose precision but point estimates remain stable.

Table 3: Estimation of the impact of expected coal prices on the share of steel units

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	BOF (2)	EAF (3)
log. expected coking coal price	-0.643***	-0.744***	-0.579***
	(0.113)	(0.112)	(0.126)
log. pre-sample mean (1960-1981)	0.681***	0.658***	0.662***
	(0.044)	(0.061)	(0.040)
year trend	yes	yes	Yes
Overidentification test			
Hansen's J chi2	7.146	6.804	7.498
p-value	0.128	0.147	0.112
Observations	555	280	275
Countries	19	19	19

Notes: The non-linear model uses GMM. The first 5 lags of the logarithm of expected coal price are used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

In our preferred specifications, we also chose to exclusively rely on coking coal prices. Estimates with steam coal prices are provided in Appendix C.4. They are almost identical for EAF. In the case of BOF, the point estimate is close but the model loses precision, which is not surprising considering that BOF units mostly rely on coking coal. Likewise, using both steam and coking coal prices at the same time does not change our overall findings, even though results lose precision due to the high correlation between steam and coking coal prices (see Appendix C.5).

The choice of the pre-sample period has also little influence on our findings: modifying the pre-sample period from 1960-1981 to 1970-1981 does not significantly alter our results (see

Appendix D.1). Likewise, switching to a fully linear model instead of using a non-linear count model does not alter our findings (see Appendix D.2).

5. Simulation of multilateral carbon markets

We now run a simulation where we quantify the effect of the introduction of a multinational carbon market on the location of steel plants and the share of EAF units in a given country at time *t*. We assume that the policy, if implemented in country *i* at time *t*, raises the price of carbon by an additional $ 31 per ton of CO2 equivalent. This figure corresponds to the current social cost of carbon as estimated in Nordhaus (2017). For simplicity, we assume that this increase in the price of carbon would be additional to any existing policies. We convert the carbon tax of $ 31/tCO2eq. into a coal price increase by assuming that a ton of coal emits 2.457/tCO2eq. (Trust, 2008). We therefore raise the expected price of coal in regulated countries by about $ 76 per ton.

We define one business-as-usual scenario and two policy scenarios. In the business as usual scenario, the policy is implemented nowhere. The first policy scenario is a scenario in which all countries agree on entering the multilateral carbon market. Therefore, we apply the coal price increase of $ 76 per ton to the 22 countries of our sample. We furthermore develop one additional policy scenario in which the carbon market is applied only in European countries. This scenario corresponds to the one where the steel industry would be strictly regulated under the EU Emissions Trading Scheme (ETS), with a much higher carbon price (of $ 31/tCO2eq.) than the one that can be observed today in the EU ETS.

The simulation uses the specifications displayed in columns 2 and 3 of Table 2: we assume that the impact of increasing coking coal prices is different for BOF and EAF units. Using these specifications, we compute the share of BOF and EAF units that would have operated in country i over the sample period (1982-2014) under the two policy scenarios, and compare this share to the one recorded in our data (which corresponds to the business-as-usual scenario). Demand for steel is assumed to be fixed in spite of the changing coal prices. Results are reported in Table 4.

In the business as usual scenario, 24.04% of plants are in North America, 23.87% are in Europe, 50.79% are in Asia, and 1.31% in other regions of the world. EAF plants represent 76.83% of North American plants, 63.36% of European plants, 50.96% of Asian plants, and 45.90% of other regions' plants.

In the scenario where the coal price increase only affects European countries, the share of steel units present in Europe goes down to 22.2%. This is a 1.7% reduction in market share. The share of EAF units would increase by 0.17% (from 63.36% to 63.53%) in Europe. The reduction in market share appears to be disproportionately high compared to the gains obtained in greening the domestic production of steel in Europe.

In the "all countries" scenario, Asian countries significantly lose market share (minus 9.7 percentage points), mostly in favor of European countries (plus 7.9 percentage points). Higher coal prices also lead to a shift towards greener production processes everywhere, in Asia particularly where the share of EAF plants would increase by 4.8 percentage points. The two phenomena are linked. The main reason why Asian countries would lose market share is because Asian firms are more coal intensive (they rely more on the BOF technology) and have built their steel industry on relatively cheaper energy. European firms are relatively less affected by the coal price increase because energy prices are already high in Europe.

Table 4: Simulation results on the location and technology of steel units under the implementation of carbon markets, pricing GHG emissions at $ 31/tCO2eq.

Indicator	Share of units over the total amount of units operative in the world			Percentage of units that are EAF		
Scenario	BAU	Europe only is regulated	All regions are regulated	BAU	Europe only is regulated	All regions are regulated
North America	24.0%	24.6%	26.2%	76.83%	76.83%	78.8%
Europe	23.9%	22.2%	31.8%	63.4%	63.5%	63.5%
Asia	50.8%	51.9%	41.1%	51.0%	51.0%	55.8%
Other	1.3%	1.3%	1.0%	45.9%	45.9%	44.3%

Notes: The simulations are run for the case of the implementation of a carbon scheme with an optimal price of carbon of $31=tCO2. Share of active units is calculated as the number of active steel-making units in a region over the total number of active units in the rest of the world. The share of EAF is calculated as the proportion of EAF units over the total number of steel-making units in a region. North America includes Canada and the US; Europe includes Germany, Turkey, Spain, Italy, France, Poland, Belgium, Czech Republic, Sweden, Finland, the Netherlands, Portugal, Switzerland and Norway; Asia includes China, Japan, Russia and India; Other regions include Australia and Chile.

These simulations are informative about the upcoming difficulties in finding common agreements on carbon markets across the globe. Our figures suggest that some European firms would relocate if the European steel industry was to comply with a more stringent carbon price, e.g. in the framework of the EU ETS. However, we also find that Asian countries have benefited from a competitive advantage because of relatively cheap energy, allowing them to rely on polluting technologies to produce steel. They would lose part of this advantage if emissions were uniformly priced worldwide as they specialized more in BOF technologies. Finally, cross-country relocation effects appear stronger than within-country changes in steel-making technologies.

6. Conclusion

The Paris Agreement, in 2015, has shown the ambition of countries to undertake a global action against climate change. The steel sector is particularly sensible to this topic as it is a major emitter of GHG emissions in the atmosphere. Given the availability of two substitutable steel-making technologies, the interest lies on the possibility, through environmental policies, to shift steel production from BOF to EAF, making it less carbon intensive.

This study aims at shedding light on the impact of an increase in coal prices on the location of steel plants and the technologies that the firms would choose to produce steel. We find that, on average, an increase of 1% in the expected price of coal reduces the share of steel-making units active in one country, compared to the rest of the world, by 0.51%. This effect seems to differ across types of production technologies: BOF units are more sensitive (minus 0.61%) than EAF ones (minus 0.43%). When we simulate the effect of regional increases in coal prices, we find that European firms would lose competitiveness if they were to unilaterally set a binding carbon price on their firms. Therefore, the risk of relocation is real for EU firms if steel making processes were more heavily taxed. Another important finding is that a uniform increase of coal prices across the globe would also have an impact on the location of steel plants. Asian firms would be more severely touched because they are the ones that rely on BOF technologies the most.

Therefore, the simulation on the European market shows that unilateral agreements may prove detrimental to national industries in industrialized countries, making the search for a multilateral agreement all the more necessary. Yet, a multilateral agreement could also have strong redistributive consequences for the steel sector. Our results suggest a multilateral agreement on taxing energy use in the steel sector could only be reached if measures were taken to guarantee that reducing GHG emissions in the industry would not strongly modify the location of production worldwide. Whereas these results mostly apply to the steel sector, they are likely to be valid for other energy-intensive sectors open to international competition, such as the cement industry.

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Appendices

A. Descriptive statistics of full dataset and pre-sample data

Table A1 provides information on the number of steel units recorded in the data for the pre-sample period (1960-1981) for the countries included in the final analysis.

Table A1: Descriptive statistics of OECD data on steel plant location and main technology used in production (1960-1981)

Period	1960-1981	
Technology	BOF	EAF
North America	48.8	143.7
Europe	56.4	83.5
Asia	105.4	76.4
Other	5.1	2.5
Total	**215.7**	**306.0**

Notes: The table reports the average number of active units of steel-making production in each region of the world. North America includes Canada and the US; Europe includes Germany, Turkey, Spain, Italy, France, Poland, Belgium, Czech Republic, Sweden, Finland, the Netherlands, Portugal, Switzerland and Norway; Asia includes China, Japan, Russia and India; Other includes Australia and Chile.

Table A2 provides information on the number of steel units recorded in the data for the full period available in the OECD data. Also countries which we couldn't match with coal prices are included here. In addition to lower data quality, the fact that BOF seems remarkably scarce in the period before 1960 could be explained by the large presence, in that time frame, of OHF which is not reported in the table. Starting from the 1960s, OHF has been almost completely phased out by BOF processes.

Table A2: Descriptive statistics of OECD data on steel plant location and main technology used in production (1900 – 2014)

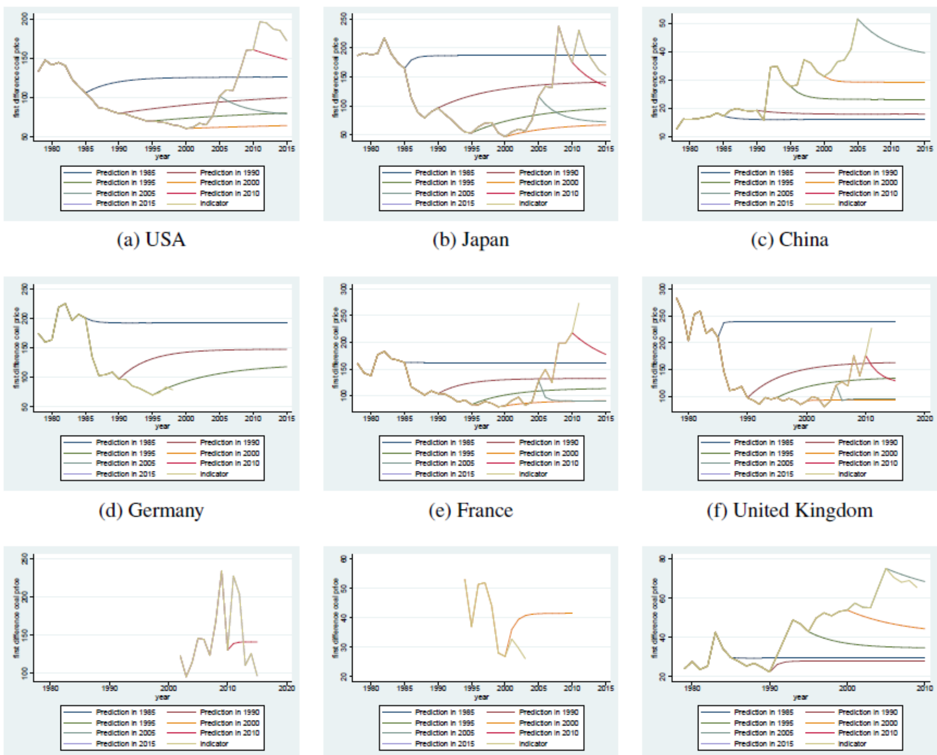
Period	Before 1960		1960-1981		1982-1990		1991-2000		2001-2014	
Technology	BOF	EAF	BOF	EAF	BOF	EAF	BOF	EAF	BOF	EAF
North America	0.2	9.4	48.8	143.7	70.3	234.8	64.8	210.0	54.3	183.3
Europe	0.6	0.4	96.0	109.0	188.7	253.3	168.9	230.7	137.6	236.9
Asia	0.1	1.8	112.8	99.5	246.3	305.8	287.2	445.0	373.0	567.4
Other	0.1	0.2	18.9	34.3	52.0	94.1	53.6	109.8	51.7	111.9
Total	**1.0**	**11.8**	**276.4**	**386.6**	**557.3**	**888.0**	**574.5**	**995.5**	**616.7**	**1099.5**

Notes: The table reports the average number of active units of steel-making production in each region of the world. North America includes Canada and the US; Europe includes Albania, Austria, Belgium, Bosnia, Bulgaria, Croatia, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Latvia, Luxembourg, Macedonia, Moldova, Netherlands, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, Ukraine, United Kingdom; Asia includes Armenia, Azerbaijan, Bangladesh, Belarus, China, Hong Kong, India, Indonesia, Iran, Iraq, Japan, Kazakhstan, North Korea, South Korea, Lebanon, Malaysia, Mongolia, Oman, Pakistan, Philippines, Qatar, Russia, Saudi Arabia, Singapore, Sri Lanka, Taiwan, Thailand, Tunisia, United Arab Emirates, Uzbekistan and Vietnam; Other includes Argentina, Australia, Brazil, Chile, Colombia, Cuba, Dominican Republic, Ecuador, El Salvador, Guatemala, Honduras, Mexico, New Zealand, Paraguay, Peru, Uruguay and Venezuela.

B. Output of ARIMA model to produce coal price expectations

Figure B1 shows, for a selection of countries, the expectations on coking coal prices computed with the ARIMA model presented in section 3. Predictions are only displayed for specific years (1995, 2000, 2005, 2010 and 2015) even though they were computed for each year and country used to run our econometric model.

Figure B1: Expected coking coal prices as predicted with the ARIMA model



(a) USA (b) Japan (c) China

(d) Germany (e) France (f) United Kingdom

(g) Brazil (h) Russia (i) India

C. Alternative specifications of coal prices

1. Using coal prices in levels and not in logarithm

Table C1 presents the estimation where the expected coal prices are included in normal values instead of the logarithmic form. Instead of equation 1, we estimate:

$$N_{s,i,t} = exp\left(\alpha + \beta p^{*}_{i,t} + \sigma \ln\left(\overline{N}_{s,i,t_i}\right) + \theta t\right) + e_{s,i,t}$$

Logically, the magnitude of the estimated betas is around 100 times smaller, but the relative effects remain stable.

Table C1: Estimation of the impact of coal prices on the share of steel units

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
expected coking coal price	-0.0053** (0.0026)	-0.0066** (0.0029)	-0.0044* (0.0023)
log. pre-sample mean (1960-1981)	0.686*** (0.042)	0.721*** (0.080)	0.650*** (0.044)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of the expected coal price is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Pre-Sample Mean is included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

2. Using the contemporaneous price of coal

Table C2 reports the estimation results obtained when using the current coal prices instead of the expected ones. Results are similar.

Table C2: Estimation of the impact of contemporaneous coal prices on the share of steel units

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	BOF (2)	EAF (3)
log. coking coal price	-0.487*** (0.148)	-0.582*** (0.168)	-0.424*** (0.141)
log. pre-sample mean (1960-1981)	0.710*** (0.035)	0.724*** (0.070)	0.677*** (0.041)
year trend	yes	yes	Yes
Observations	787	395	392
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of the logarithm of contemporaneous coal price is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

3. Using distributed lags for the price of coal

Table C3 provides the results of a distributed lag model in which we have included the first 2 lags of the expected price of coal. We use the first to third lags of expected coal prices as instrument. If we add up the effects of the current expected coal price with the ones of its lags, we obtain an overall effect of -0.67% which is not far away from the effect found in the basic regression. This formulation is therefore consistent with our baseline specification, even though it loses precision.

Table C3: Estimation of the impact of coal prices on the share of steel units using a distributed lag model with 2 lags

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	-0.076 (0.277)	-0.375 (0.374)	0.029 (0.304)
lag_1(log. expected coking coal price)	-0.413 (0.462)	-0.356 (0.520)	-0.434 (0.516)
lag_2(log. expected coking coal price)	-0.178 (0.187)	-0.106 (0.169)	-0.157 (0.200)
log. pre-sample mean (1960-1971)	0.681*** (0.045)	0.688*** (0.077)	0.647*** (0.050)
year trend	Yes	Yes	Yes
Observations	637	300	295
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of each independent variable is used as instrument. The models include a time trend. The pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

4. Using steam coal prices instead of coking coal prices

In Table C4, we use expected steam coal prices instead of expected coking coal ones. As this type of coal is only used in EAF processes, we find a significantly negative effect for the EAF estimation. The model instruments for coal prices and, therefore, may correct for measurement error in the case of BOF (who uses coking coal). The point estimate for BOF is negative and larger than for EAF units, even though only statistically significant at 10%.

Table C4: Estimation of the impact of expected coal prices on the share of steel units using the first lag of the logarithm of expected steam coal prices as instrument

Dependent Variable (Share Units of Steel Production)	Non-Linear Model		
	All (1)	BOF (2)	EAF (3)
log. expected steam coal price	-0.511** (0.257)	-0.561* (0.306)	-0.470** (0.221)
log. pre-sample mean (1960-1981)	0.654*** (0.056)	0.699*** (0.093)	0.629*** (0.057)
year trend	yes	yes	Yes
Observations	675	327	348
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of the logarithm of expected coal price is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

5. Using both coking coal and steam coal prices

Table C5 presents the results of the estimation where both coking coal prices and steam coal prices are used. The overall findings remain the same: increasing the price of coal may discourage more BOF production rather than EAF. Nevertheless, except for the coefficient associated to coking coal in the BOF estimation, all the coefficients are now insignificant. This may be attributed to the loss of precision due to multicollinearity between coking and steam coal prices.

Table C5: Estimation of the impact of both expected coking and steam coal prices on the share of steel units

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	-0.548 (0.370)	-0.866** (0.384)	-0.377 (0.371)
log. expected steam coal price	0.033 (0.190)	0.252 (0.223)	-0.080 (0.216)
log. pre-sample mean (1960-1981)	0.691*** (0.046)	0.709*** (0.069)	0.649*** (0.055)
year trend	yes	yes	yes
Observations	583	294	289
Countries	19	19	19

Notes: The non-linear model uses GMM. The first lag of each dependent variable is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

6. Using coking coal price / electricity price ratio

The choice of the main independent variable – the price of coal – seems natural, but an interesting extension could be to use the price ratio between expected coking coal price and expected electricity price. Indeed, the decision of using BOF rather than EAF seemingly depends on the difference between coal and electricity prices, since BOF uses coal, but EAF uses electricity. Electricity used to operate EAF plants is usually produced on-site using coal, but this could vary according to the energy mix of the country of operation. Including the price ratio between the two should capture this possibility. Table C6 presents the results under this specification. They appear even stronger than in the baseline scenario. An increase of 1% in the ratio, which could be associated either with an increase in expected coking coal price or a decrease in expected electricity price, reduces the share of BOF steel-making units active in a country, compared to the rest of the world, by 3.2%, while it only reduces the share of EAF by 2.52%. Again, we find evidence of a directed technical change effect.

Table C6: Estimation of the impact of expected coking coal price / expected electricity price ratio on the share of steel units

Dependent Variable (Share Units of Steel Production)	Non-Linear Model		
	All (1)	BOF (2)	EAF (3)
log. (expected coking coal price/ expected electricity price ratio)	-2.579*** (0.870)	-3.180** (0.976)	-2.520*** (0.665)
log. pre-sample mean (1960-1981)	0.782*** (0.052)	0.723*** (0.104)	0.763*** (0.052)
year trend	yes	yes	yes
Observations	671	338	333
Countries	19	19	19

Notes: The non-linear model uses GMM. The first lag of each dependent variable is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

7. Adding more controls

Table C7a presents the results of the estimation where the logarithm of GDP is added, as an additional control, to the baseline specification. The main findings remain the same. The GDP coefficient is not significantly different from 0, indicating that the economic development of a country does not give an a priori advantage in investing in one steel-making technology rather than the other.

Table C7a: Estimation of the impact expected coking coal prices on the share of steel units, adding GDP

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	-0.439*** (0.132)	-0.494*** (0.120)	-0.406*** (0.142)
log. pre-sample mean (1960-1981)	0.816*** (0.060)	0.899*** (0.105)	0.722*** (0.047)
log.GDP	-0.121 (0.089)	-0.150 (0.089)	-0.059 (0.087)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of each dependent variable is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

Table C6b tests for the presence of non-linear effects. The logarithm of the squared price of coal is added to the baseline estimation. Results are even stronger in this scenario. An increase of 1% in the expected price of coal reduces the share of BOF steel-making units active in a country, compared to the rest of the world, by 2.3%, while it only reduces the share of EAF by 1.77%. The positive second order coefficient indicates a convexity in the relation between the share of steel-making units and the expected coking coal price. It means that the maximum decrease in share of active units may be reached with a medium decrease in coal price. In this specification the two coefficients appear significantly different from each other at 0.05 significance level.

Table C7b: Estimation of the impact expected coking coal prices on the share of steel units, adding a non-linear effect

Dependent Variable (Share Units of Steel Production)	Non-Linear Model		
	All	BOF	EAF
	(1)	(2)	(3)
log. expected coking coal price	-2.095***	-2.304***	-1.775***
	(0.500)	(0.448)	(0.565)
log. pre-sample mean (1960-1981)	0.731***	0.755***	0.690***
	(0.036)	(0.066)	(0.038)
log. expected coking coal price_sq	0.195***	0.210***	0.164***
	(0.070)	(0.065)	(0.076)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of each dependent variable is used as instrument. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

D. Choice of estimation method

1. Using a different pre-sample period

Using a shorter pre-sample period starting in 1970 has little influence on the results obtained (see Table D1 below).

Table D1: Estimation of the impact of expected coal prices on the share of steel units, pre-sample starting in 1970

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	BOF (2)	EAF (3)
log. expected coking coal price	-0.418*** (0.089)	-0.486*** (0.073)	-0.399*** (0.122)
log. pre-sample mean (1970-1981)	0.776*** (0.047)	0.756*** (0.056)	0.751*** (0.050)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The first lag of the logarithm of expected coal price is used as instrument. The models include a time trend. Pre-sample ranges from 1970 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and ***__ respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

2. Linear version of the pre-sample mean estimator

The linear version of the pre-sample estimator, shown in Table D2, uses a 2SLS procedure. Given that we are dealing with a count model, we lose efficiency when we switch from the non-linear to the linear setting. Nevertheless, the 2SLS provides similar results and allows computing a weak identification test to verify the strength of the instrument.

Table D2: Estimation of the impact of expected coal prices on the share of steel units, linear model

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	-0.034** (0.015)	-0.034** (0.016)	-0.033** (0.014)
log. pre-sample mean (1960-1981)	0.439*** (0.025)	0.459*** (0.094)	0.431*** (0.020)
year dummy	yes	Yes	yes
Weak Identification Test			
Kleibergen-Paap rk Wald F statistic	2816.23	3056.82	2308.95
Stock-Yogo maximum bias	<10%	<10%	<10%
Observations	555	280	275
Countries	19	19	19

Notes: The linear model uses IV 2SLS. The models include a time dummy. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

3. Results with a fixed effect model

In Table D3, we present the results obtained when using a fixed-effect estimator. This model assumes that expected coking coal prices are fully exogenous. Results are biased and the model is inconsistent.

Table D3: Estimation of the impact of expected coal prices on the share of steel units, fixed-effect model

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	0.223* (0.132)	0.299** (0.137)	0.163 (0.129)
year trend	yes	yes	Yes
Observations	767	386	381
Countries	22	22	22

Notes: The non-linear model uses GMM. The models include a time trend. Independent variable is included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

4. Results with a first difference estimator

Tables D4.a and D4.b feature first-difference estimators. Table D4.a uses a transformed model based on Chamberlain (1992) and Wooldridge (1997). We use the second lagged difference of the independent variable as an instrument. In this case, the estimated effect of coal price on steel production is negative. We find a stronger effect for EAF than BOF. Nevertheless, all these effects are not statistically different from 0. This is not surprising since we know that results from the first-difference estimators are usually inefficient.

Table D4.a: Estimation of the impact of expected coal prices on the share of steel units, model in first difference based on Chamberlain (1992) and Wooldridge (1997)

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	 BOF (2)	 EAF (3)
log. expected coking coal price	-0.007 (0.036)	-0.029 (0.077)	-0.070 (0.091)
year trend	yes	Yes	Yes
Observations	637	321	316
Countries	22	22	22

Notes: The non-linear model uses GMM. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

The results of table D4.a are also likely to be biased towards a first differenced model where we would assume that the coal price is exogenous (as shown in Staiger and Stock, 1997; and Blundell and Bond, 1998). Such a first differenced model is reported in Table D4.b. Results are inconsistent due to the violation of the exogeneity assumption. Here, the coefficient for BOF is positive and higher than for EAF, so the small sample bias is likely to explain why, in table D5.a, we found that the negative coefficient for EAF was higher in magnitude than the one for BOF.

Table D4.b: Estimation of the impact of expected coal prices on the share of steel units, model in first difference with assumption of exogenous coal prices

Dependent Variable (Share Units of Steel Production)	Non-Linear Model All (1)	BOF (2)	EAF (3)
log. expected coking coal price	0.043 (0.030)	0.081* (0.044)	0.025 (0.032)
year trend	yes	yes	yes
Observations	723	364	359
Countries	22	22	22

Notes: The non-linear model uses GMM. The models include a time trend. Pre-sample ranges from 1960 to 1981. Independent variables are included in logarithmic form. Cluster-robust standard errors in parentheses. Clusters are set at country level. *, ** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.