# Do Firms Innovate when they can Relocate? Evidence from the Steel Industry *

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**Abstract**

The steel industry is the largest industrial consumer of energy and it is among the top polluting sectors worldwide. We want to study how this industry responds to tights in the main input price, namely coal. With a novel dataset on steel plants location worldwide from 1960 to 2014, we are able to distinguish between a green, Electric Arc Furnace, and a dirty, Basic Oxygen Furnace, steel-making technology, and to follow the evolution of their adoption across different countries over time. Using a pre-sample mean GMM estimator to correct for the endogeneity between production choices and inputs' prices, we find that, an incrase by 1% in coal price reduces the number of active BOF units by 0.67% while only by 0.45% the number of EAF ones. Running simulations with the estimated elasticities, we show that differentiated carbon prices across regions may mitigate the risk of relocation and encourage countries to join a global carbon market which can promote a radical change in paradigms in the industry, shifting its production from a pollution-intensive to a recycling-based one.

**Keywords**: Steel, Pollution Haven Effect, Induced Innovation Hypothesis, Firm Relocation, Technology Adoption, Technological Change

**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 a 2°C increase. Unfortunately, the 5th IPCC report shows that current environmental policies are not sufficient to reach this target. Economists have long argued that the most effective policy to achieve it would be a realignment of self-interest through common commitments, either a global price of carbon or a global carbon market (e.g. Stoft et al. (2013) and Weitzman (2014). Extensive international discussions have so far, however, not been successful in encouraging the formation of such a common commitment.[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 (e.g. Aldy and Pizer (2015), Martin et al. (2014), Santamaria et al. (2014),Kellenberg (2009) and Paltsev (2001)). The extent to which firms may prefer to comply with regulation and adapt their production processes or relocate to countries with looser environmental regulation is an empirical question of primary relevance in the implementation of carbon markets. In this paper, we estimate the effect of changes in coal price expectations on steel plant location and on the main technology used in production.

The steel industry is particularly relevant to assess the role of energy taxation in climate change mitigation. Steel is one of the most energy intensive industry and the largest consumer of energy: it represents 27% of all greenhouse gas emissions from industry worldwide (IEA, 2017).[3] Looking

[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).

[3]In 1990, steel industrys 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

jointly at the effect of energy price shocks on plant location and technological preferences constitutes the main contribution of this paper. The two are likely to interact since changes of location may be driven by the availability of low environmental standards in some countries. Evidence that energy prices foster the adoption of cleaner technologies has been found in very diverse industry contexts (e.g. Cohen et al. (2017); Aghion et al. (2016); Popp (2002); Dechezlepretre et al. (2011); Popp (2006); Brunnermeier and Cohen (2003); Newell et al. (1999); Jaffe and Palmer (1997); Lanjouw and Mody (1996)). However, none of these papers consider plant location and technological choice as simultaneous decisions. Likewise, studies focusing on relocation tend to give little attention to technological choices (e.g. Aldy and Pizer (2015); Kellenberg (2009); Wagner and Timmins (2009); Ederington et al. (2005); Jeppesen et al. (2002); Frederiksson and Millimet (2002)).

We directly estimate the impact of an increase in coal price expectations on the number of steel producing units located in a country, separately evaluating this figure according to the technology they use to produce steel. We use steel plant data collected by the OECD and covering 22 countries, representing around around 82% of the steel produced worldwide,[4] for the period 1960-2014. 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 firm resorts to BOF and/or EAF, allowing us to produce country aggregates by technology. We match the OECD data on steel plants with coal price statistics from the International Energy Agency and Chinese Ministry of Coal integrated with Bohai-Rim Price Index, covering all the 22 countries for the period 1978-2014.

We find that an increase in coal prices at national level have a negative effect on the size of steel

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

manufacturing in a country. In our preferred specification, a 1% increase in coal prices reduces the number of BOF units by around 0.67% and the amount of EAF units by around 0.45%. 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 CO2 emissions at $\$31/tCO2eq$. This is the estimate of the current social cost of CO2 in Nordhaus (2017). We assess the impact of two different scenarios that depend on the list of countries that would join this carbon market: a) all countries join the carbon market; b) only European countries join. 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 all the 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 Europe implements a carbon scheme, we observe a non-negligible shift in production from the countries that have joined the carbon market to the non-participating countries. We observe a shift in production also in the case where a uniform carbon tax is applied worldwide, particularly from Asian countries to other regions of the world. This is due to the fact that, historically, Asian firms have built their comparative advantage on cheap energy prices. Therefore, when the global carbon tax is implemented these firms are more affected than European and North American ones which already faced relatively higher coal prices in the past. Nevertheless, this shift is smaller for the case when a global carbon tax is applied rather than for the case when only few countries join the carbon scheme. These findings have strong policy relevance. We propose, as a viable way to promote a green technological shift in the steel industry, the implementation of a global carbon market with differentiated carbon prices. If well balanced, differentiated carbon prices may mitigate the relocation risk, inducing countries to join the global carbon scheme. Similar effect may apply to other highly energy intensive also strongly exposed to international competition, such as cement or the chemical industry.

All these results have been obtained from an econometric setting that circumvents several difficulties. First, 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 estimate the impact of price expectations, and not coal prices, on the size of steel manufacturing. To do so, we compute national average coal price expectations with autoregressive integrated moving average models (ARIMA). This allows us to produce expectations about future coal prices that take into account basic knowledge of previous energy price trends by manufacturers. Second, the steel industry is the largest buyer of coal and we can expect that changes in the size of the industry directly impacts coal prices. Therefore, we face a classical supply and demand simultaneity problem. Resolving this problem is complex because steel manufacturing and coal extraction are closely related, and both tend to be strongly time-persistent. Powerful instruments that explain well coal price changes and are not correlated with both current and past shocks on the size of the steel industry in a country may not exist.

We adopt an estimation technique that tolerates pre-determined variables as instruments, i.e. the lags of coal prices. While this is not possible with standard fixed effect approaches, pre-determined variables can be used as instruments with first-differenced estimators. However, these estimators are inefficient under time-persistence and can reveal to be strongly biased when applied to small samples. Instead, we rely on the pre-sample mean estimator developed 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 1960-1978 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 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 such as the definition taken for energy price expectations, the choice of functional form, or the addition of deeper lags of coal prices as instruments.

The rest of the paper is structured as follows. Section 2 examines in depth the existing literature related to the paper. Section 3 presents the data and provides a brief overview of the steel industry. Section 4 presents our estimation technique. Section 5 comments on the results and the main robustness checks performed. Section 6 presents our simulation exercise and section 7 concludes.

## 2. Literature Review

The theoretical studies on polluting industries' relocation after the implementation of a carbon tax usually rely on a modelling approach, making use of computable general equilibrium (CGE) models to look at the effects of the introduction of major carbon abatement policies (e.g. the Kyoto Protocol (Paltsev, 2001), the EU ETS (Santamaria et al., 2014), US-only carbon tax (Aldy and Pizer, 2015)) on inter-state leakages. Findings are ambiguous. Paltsev (2001) points out that leakages from energy-intensive sectors are sizeable. On the other hand, Aldy and Pizer (2015) find that leakages from these industries are rather small, roughly 1% of production shift overseas. Santamaria et al. (2014) stress a high variability depending on the sector considered: cement and oil refining appear to have higher exposure to leakages than steel. All these divergent outcomes are explained by the fact that, while informative, these CGE models build on assumed rather than estimated parameters which makes them stiff and highly dependent on initial assumptions. Additionally, they analyse different target policies. This makes them extremely tied with the national context analyzed and difficult to apply elsewhere. We overcome these flaw by building our simulations on empirical evidences obtained from the analysis of the 22 major steel-making countries for the years 1978-2014.

A more empirical approach related to the study of firms relocation can be identified in the literature. Jeppesen et al. (2002) provides a summary of early studies that principally look at the effect of an increase in abatement costs on changes in trade flow or foreign direct investment. These studies find no or marginally significant effect. Several studies evaluate ways in which strategic and non-strategic trade policies may distort environmental policy as a potential path of pollution haven. Frederiksson and Millimet (2002) finds that various US states set environmental regulations based on the regulations of neighboring states, implying that direct neighbors or regional neighbors affect decentralized decision making. This influence is stronger when the neighbor already has higher abatement costs. In contrary to a pollution haven effect, however, they found that an increase in abatement cost in a neighboring state led to a higher increase in abatement cost in own state, when the regulations in the neighboring state is already stringent. Wagner and Timmins (2009) enhanced previous studies of pollution haven effect by incorporating agglomeration externalities in the destination countries. Using longitudinal data on outward FDI flow of German manufacturing industries, they find pollution haven effect in the chemical industry, but not in other industries such as primary metals or paper. Kellenberg (2009) finds evidences 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. Ederington et al. (2005) measure a significant effect of pollution abatement costs on imports from developing countries and in pollution-intensive industries only if they are geographically mobile. However none of these studies combine the analysis of firms' relocation with the idea of technology adoption, which will be the main contribution of our paper.

Indeed a separate strand of literature focuses solely on technological choices. Both Jaffe and Palmer (1997) and Brunnermeier and Cohen (2003) find a correlation over time of pollution abatement control expenditure and level of R&D spending, suggesting that increased expenditures may modestly stimulate R&D activities with the motivation to reduce cost. Using US patent data from 1970 to 1994, Popp (2002) estimated a long-run elasticity of energy patenting with respect to energy prices to be 0.354 and significant. Using disaggregated patent data, Popp (2006) finds significant increases in patents related to SO2 and NO emission reduction in response to environmental regulation in US, Japan and Germany. He argues that R&D spending as a measure of innovation is too broad, and may mask the effect that can be seen from disaggregated analyses. Popp (2002) also finds that mean lag response between patenting and energy prices is 3.71 years, suggesting that innovation response happens quickly. Furthermore, such innovation takes place predominantly in developed countries. Dechezlepretre et al. (2011) studies a broad range of climate friendly innovations, including renewable energy, carbon capture and storage, and energy efficiency technologies for various industries using patent data from 1978 to 2005 for 76 countries. They concur with Lanjouw and Mody (1996) that two-thirds of innovation in their sample comes from US, Japan and Germany. Testing the effect of energy prices on product innovation in the consumer sector, Newell et al. (1999) studies the effect of energy prices and government regulation on air conditioning and water-heating in the US from 1958 to 1993. He finds that increased energy prices did not extend the frontier (i.e., affect the rate of innovation), but moved the bundle of product features to a different point on the frontier towards energy efficiency (i.e., affect the direction of innovation). Cohen et al. (2017) studies the effect of energy prices on product innovation in the UK refrigerator market, and found a 10% increase in electricity prices reduces average energy consumption of refrigerators by 2%. Using data from European Patent Offices World Patent Statistics database, Aghion et al. (2016) finds that in the automobile industry, high fuel price redirects firms investment away from dirty and towards clean innovation. Our contribution to this strand is twofold: on the one hand we broaden the scope of our study to 22 big steel producers, not restricting our attention to only fone or few countries; on the other hand we complement the analysis of technological change with the possibility of plant relocation which, we argue, need to be treated as simultaneous decisions. We are only aware of the study by Mathiesen and Maestad (2004) which 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. Differently from them we estimate these elasticities, by making use of a 35-years long panel of data.

In the steel sector, several authors have looked at technology responsiveness to energy prices, but 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. With respect to these papers, we propose an improved identification strategy which allows us to treat the simultaneity between production choices and inputs' prices. To this effect, we employ a pre-sample mean estimator.

## 3. Data and Descriptive Statistics

Our dataset combines two types of information: 1) steel plant location differentiated by technology, which are used to geographically localized steel production, and 2) coal price.

**Steel Data** The main dataset is assembled and made available by the OECD. This dataset features steel plants location (with their openings and their closures) starting from the beginning of the 20th century. The most disaggregated layer of observation in the database is at the unit level: within each plant there could be simultaneously multiple active units of production. We have information about the production technology used within the unit that could be either EAF or BOF.

The predominant technologies in steel making today are BOF and EAF. BOF is a technology that came into wide adoption in the 1960s.[5] 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. For BOF, the blast furnace and other combustion processes contribute 88% of $CO_2$ emission, while indirect electricity consumption contributes 12%. [6] (EPA, 2012; OECD, 2013; IEA, 2012).

The EAF is a different steel-making process which uses as main input ferrous scrap, instead of raw materials like its predecessors (Giarratani et al., 2013). Additionally, it makes use of electricity to convert scrap into new steel. Steel firms typically produce electricity within their own plants, using steam coal which can therefore be considered, indirectly, still part of the production process. 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.[7] At the beginning of the 20th century it was difficult to

[5] The Open Heart Furnace (OHF), a steel-making process invented in the 19th century, has been for many years the primary process used in steel production. 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 2 BOFs are required to replace 12 OHFs. Given this phase-out we exclude OHF from the analysis.

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

[7] Steel scrap can have different sources: "home scrap" generated within the plant (nowadays it is not sufficient

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 '70s it started to spread as an almost-perfect substitute to BOF. The main source of emissions in the EAF process is electricity, 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.

EAF plants have typically a smaller capacity than BOF, but our data does not feature the production capacity of each plant. In terms of GHG emissions, EAF plants emit, for the same amount of steel produced, 4 time less than their BOF counterparts (OECD, 2013; IEA, 2012). Table 1 summarize the main characteristics of both processes. In the remaining analysis, EAF is considered as a green alternative to the rather dirty BOF.

TABLE 1: STEEL PROCESS CHARACTERISTICS BY TECHNOLOGY

| | BOF (Primary) | EAF (Recycling) |
|---|---|---|
| Main direct inputs | Coking Coal, Iron ore | Steam Coal, Scrap |
| Virgin material per ton of steel produced | 2.8 to 3 tonnes | 0.2 to 0.3 tonnes |
| Energy intensity (Gj/t) | 21 to 25 | 8 to 11 |
| Emission intensity (t $CO_2/t$) | 2.1 to 2.5 | 0.4 to 0.7 |

Source: "Impact of energy market developments on the steel industry ", OECD (2013)

The diffusion of these two steel-making technologies crucially depends on the availability of raw materials. EAF remains a prerogative of more developed countries where scrap is sufficiently available to sustain the production, while developing countries typically have an advantage on cheap resource extraction due to lack of environmental regulation. Figure 1 shows the percentage of EAF and BOF on the total number of active units of steel production for the regions of the world.

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).

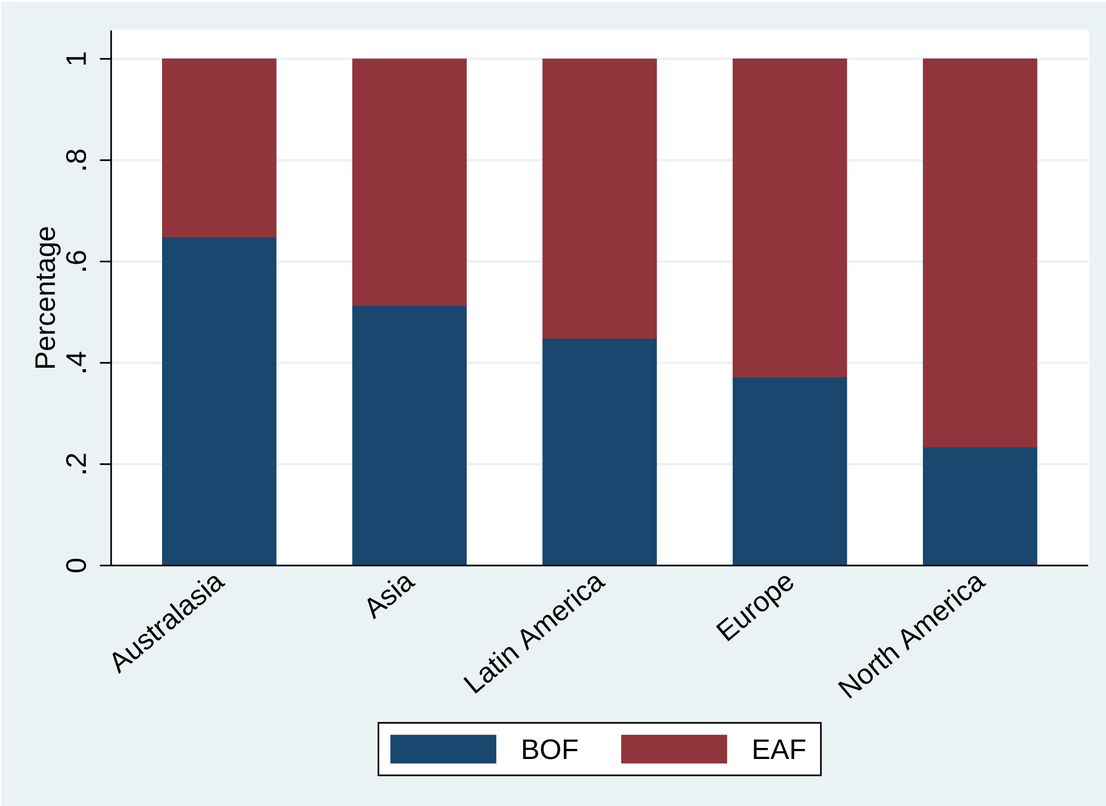


Figure 1: Percentage of BOF and EAF active units for steel production, regional decomposition.

Australasia and Asia exhibit a high percentage of BOF in the regional technology composition.[8] On the contrary, in Europe, Latin and North America the ratio of EAF over total active units greatly exceeds that of BOF.

There are two ways of cutting the emissions in the steel-making process. The first and more apparent one relates to technology switching: choosing EAF rather than BOF. It does not respond instantaneously to market changes due to high initial sunk costs in the establishment of the plant, but it reacts to long term expectation on market variables, such as inputs' prices or regulatory changes. The second and less evident relates to improvements implemented within the production process itself (for example fuel switching or inputs' substitution). It is easier to use in the short-term and therefore suitable to be used as a buffer against unexpected changes in regulatory standards which require to cut down emissions. A limitation of this study is that we are unable to control for the second adjustment as we lack of intra-firm data related to specific characteristics

[8]Remember that typically EAF plants are much smaller than BOF ones. It means that, in Australasia and Asia, the majority of steel production can still be attributed to BOF.

of the production processes. Nevertheless, we are able to capture the substitution between EAF and BOF following an increase in the price of coal. This represents the technology shift of main interest happening within the industry nowadays.

**Coal Price**: We collected coal prices from two data sources: International Energy Agency (IEA)[9] and Chinese Ministry of Coal integrated with Bohai-Rim Price Index[10]. 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 iron-making, or the use of coking coal. However, they are reliant on electricity generated by coal-fired power plants. Around 150kg of coal is used to produce 1000kg of steel (WCA, 2017).

Coking coal and steam coal prices strongly correlate (59.50% correlation coefficient). To avoid multicollinearity we decide to include only one of them in our estimation. Since coking coal is the major pollutant in steel-making processes we restrict our attention to its effect on steel plants location choices.[11] All prices are converted into constant 2010 USD/tonne.[12]. Figure 2 features the evolution of coking coal prices in different regions of the world across the years. Fossil fuel prices have been consistently lower in Asia rather than Europe or North America.

[9]We collected the total price charged to the industrial sector

[10]We would like to thank Xiaojing Zhou for the precious help in collecting these data.

[11]A robustness check with steam coal prices instrad of coking coal prices is reported in Table B5 of Appendix B.

[12]Please refere to Appendix A for a detailed description on how we built the dataset.

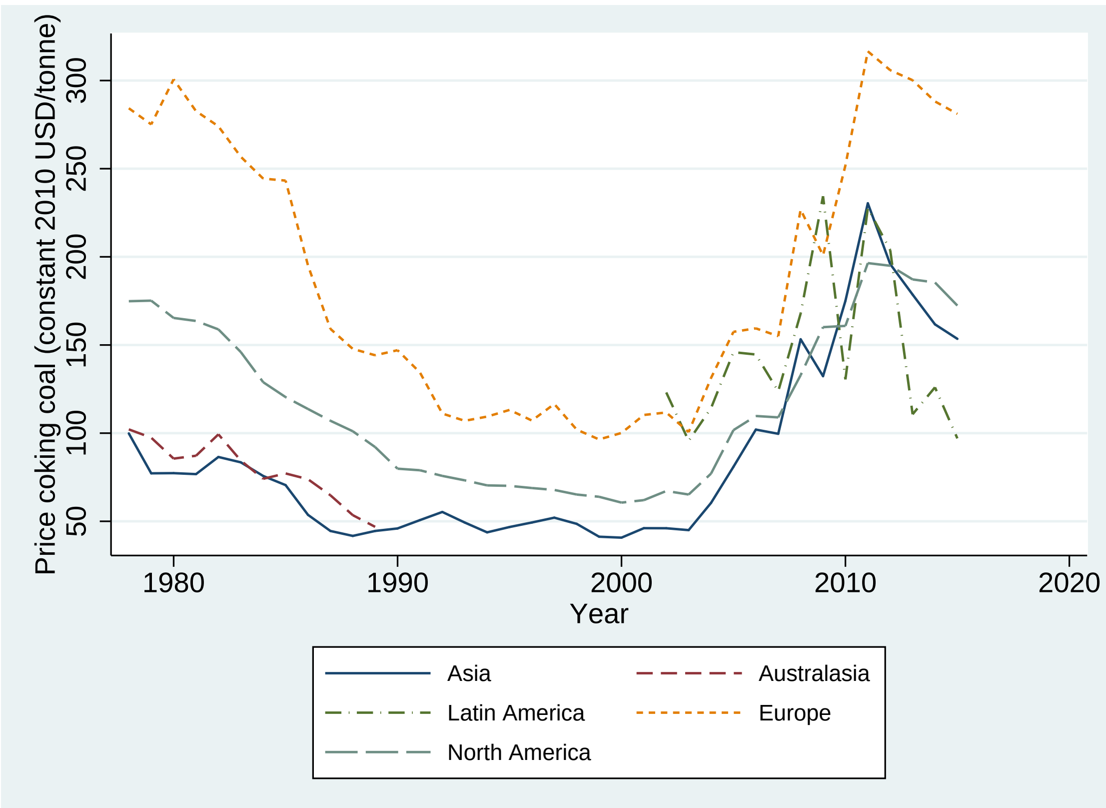


Figure 2: Coking coal price evolution, regional decomposition.

Table 2: Summary Statistics

| Variable | Active BOF Units | Active EAF Units | Coking Coal Price |
|---|---|---|---|
| Variable Description | Number of active units producing steel with BOF technology | Number of active units producing steel with EAF technology | Price of coking coal in constant 2010 USD/tonne |
| Source | OECD | OECD | IEA and Chinese Ministry of Coal/ Bohai-Rim Price Index |
| All Sample - Mean (S.D) | 73.55 (99.70) | 109.85 (116.52) | 124.62 (68.06) |
| North America - Mean (S.D) | 63.05 (8.20) | 206.22 (21.46) | 114.37 (45.68) |
| Europe - Mean (S.D) | 97.49 (12.37) | 167.87 (9.65) | 182.66 (75.38) |
| Asia - Mean (S.D) | 272.57 (62.44) | 278.60 (68.85) | 82.78 (50.29) |
| Australasia - Mean (S.D) | 6.19 (1.00) | 4.60 (0.55) | 78.87 (17.50) |
| Latin America - Mean (S.D) | 2.00 (0) | 1.81 (0.46) | 149.85 (45.25) |

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; Australasia includes Australia; Latin America includes Chile.

Table 2 summarizes the statistics for the variables under analysis. Prices of coking coal are expressed in constant 2010 USD/tonne. Data are presented first in aggregate for the full sample, and then disaggregated across regions of the world. The table shows the average number of active units of BOF and EAF, and the average price of coking coal which can be observed each year in the regions present in our sample. The bigger concentration of steel production units is registered in Asia, Europe and North America. Coal prices are, on average, higher in Europe, Latin and North America.

## 4. Methodology

In this Section we, first, discuss the characteristics of the ARIMA model used to generate the future expected coal prices. Secondly, we present our empirical strategy to identify the effect of coal prices on steel plant location.

### *4.1 ARIMA model*

Manufactoring companies are likely not to base their production decision on current inputs' prices, but rather take in consideration their expectations about the future. This is particularly true for a sector like the steel one with big initial sunk investments and long-lifetime investments, where changes of production choices cannot happen overnight and are going to take multiple years to be put in place. Measuring the expected coal price is more problematic as we only observe real prices. As a benchmark, we consider that a perfectly rational consumer forecasts future prices based on information about past prices. We approximate this calculation process by an autoregressive integrated moving-average model (ARIMA) on yearly data of real coal prices for the previous 10 years. A good fit for our data is a first-order autoregressive model:[13]

$$p_{i,t} = \mu + \gamma p_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where the price of coal $p$ in each country $i$ is regressed on itself lagged by one period. This technique allows us to recreate the entire flow of future expected prices. The model is used recurrently to make forecasts, using data observed in the previous periods to calculate new predictions. We re-estimate this model for each year to allow steel companies to use the previous 10 years data that are observed at each time period in a specific country (e.g. the price expectations for companies in 2015 are based on prices observed between 2005 and 2014). This implies that the model is updated each year based on previous market data.[14] We use predictions generated with this ARIMA model ($p^*_{i,t}$), rather than real prices ($p_{i,t}$), as dependent variables in our basic estimation. Appendix B reports a series of robustness checks where the contemporaneous coal price (see Table B2)and the distributed lag models (see Table B3) are used as main independent variable in place of expected prices.

[13]We omit for simplicity the country underscript, but the following model is applied to time series of coal price in each country $i$.

[14]More detailed statistics for the ARIMA estimations are reported in Appendix A.

### 4.2 Empirical Model

Hereafter, we develop an empirical strategy that allows estimating the impact of coal prices on the size of steel manufacturing in a country. Our general approach consists in applying a count model with the total number $N$ of steel plants using technology $s \in \{BOF; EAF\}$ in country $i$ during year $t$ 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. [15] The expected price of coal, denoted $p^*_{i,t}$, constitutes the independent variable of interest of our model; this variable is endogenous.

$$N_{i,t,s} = f(p^*_{i,t}) \tag{2}$$

The total demand for coal in country $i$ and at time $t$ 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 $t$, which we denote $p_{i,t}$. 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 side, 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.

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 instrument 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

[15] 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).

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 may not hold. For example, steel is used in construction, and shocks on the construction sector should translate in a simultaneous increase of both energy demand and steel demand.

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 strict exogeneity assumption, 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 of 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 biased and inefficient estimates in the present case. In such an econometric context, Blundell et al. (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 et al. (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 1960, while our data on $p^*_{i,t}$ starts in 1978. We have 18 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 et al. (2002). We estimate the following count model:

$$N_{s,i,t} = exp(\alpha + \beta ln(p^*_{i,t}) + \sigma ln(\overline{N}_{s,i,t_i}) + e_{s,i,t} \tag{3}$$

Where $ln(\overline{N}_{s,i,t_i})$ is natural logarithm of the pre-sample mean of $N_{s,i,t}$ over $\{t_i;t_0\}$, $ln(p^*_{i,t})$ is the natural logarithm of the expected coal prices[16] and $e_{s,i,t}$ is the error term. This expression can be estimated using GMM. $\overline{N}_{s,i,t_i}$ is used as an instrument. We need an additional instrument to correct for the endogeneity of $p^*_{i,t}$. In the present case, the lags of $p^*_{i,t}$ 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 $p^*_{i,t-1}$ to instrument for $p^*_{i,t}$.

We furthermore run a series of robustness checks. First, we expand the number of lags used as instruments, and run the model with up to five lags of $p^*_{i,t}$ 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. In addition, we also use lags of cost shifters as instruments in alternative specifications (see Table B3 in Appendix B). We furthermore report and discuss the results obtained with pooled OLS, a fixed effect model, a first difference model and a linear version of our pre-sample mean estimator respectively in Tables B6 and B1 of Appendix B. In the next Section we present the results of the estimation along with several robustness checks to prove their validity.

## 5. Results and Robustness

### *5.1 Results*

Table 3 presents the results of the estimation of equation 3 is estimated through GMM. We consider, as pre-sample period, the interval (1960-1978). The lagged value of the expected price of

[16] A robustness check with the expected coal prices, not in logarithmic form, is reported in Table B4 of Appendix B.

Table 3: Pre-Sample Mean Estimation

| Dependent Variable (Units of Steel Production) | Non-Linear Model All (1) | BOF (2) | EAF (3) |
|---|---|---|---|
| Expected Coking Coal Price | -0.546*** | -0.666*** | -0.455*** |
| | (0.139) | (0.150) | (0.136) |
| Pre-Sample Mean | 0.684*** | 0.731*** | 0.641*** |
| | (0.042) | (0.073) | (0.043) |
| Year Trend | Yes | Yes | Yes |
| Observations | 715 | 356 | 359 |
| Countries | 22 | 22 | 22 |

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

coal is used as instrument in all the specifications. We first analyse the full sample (column 1) and then we distinguish between BOF (column 2) and EAF (column 3) technology. From the estimation we infer that, overall, a 1% increase in coal price expectation would cause a decrease in active steel-making units by around 0.55%. If we look at the two technologies separately, we recognize that the impact is much bigger for BOF plants, 0.67% reduction (95% CI is 0.37%-0.91%), rather than EAF plants, 0.45% reduction (95% CI is 0.17%-0.78%). These effects are proved to be different from each other [17]. This translates into a reduction of the energy intensity of the overall steel-making processes by 0.6%[18] which is much bigger than the 0.12% found in Flues et al. (2015). The bigger impact found in our analysis may be due to lack of endogeneity treatment in the precedent paper. Additionally, we extend the analysis to non-European countries particularly Asian, Australasian and Latin American ones which have, on average, a lower price

[17]We run a test on the hypothesis that $\beta_{BOF} > \beta_{EAF}$; the test results significant at $p < 0.16$ with a chi2 value of 1.98.

[18]To calculate this number we apply to the average emission intesity of BOF, 2.3 t CO2/ t, and EAF, 0.55 t CO2/ t, (OECD, 2013) the estimated coefficients, obtaining new emission intensities for BOF, 2.285 t CO2/ t, and EAF, 0.548 t CO2/ t.

of coal and a bigger number of BOF units. This corroborates the hypothesis that an increase in coal price would impact the dirty technology much more than the clean one, finding evidences of the induced innovation hypothesis. Finally, in all the specifications, $\phi$ is found to be positive and significant, corroborating the presence of time persistence in the data.

### *5.2 Robustness*

Our findings are validated by a series of robustness checks. First of all, we expand the set of instruments, including not only the first lag, but the first five lags of the expected coal price in the regression. In this way, a bigger portion of past information is used to instrument the expected coal prices of today, making it more unlikely that the instrument will correlate with contemporaneous shocks and therefore better satisfying the exclusion restriction. Also, having more instruments allows us to run the overidentification test.

Table 4: Pre-Sample Mean Estimation, multiple lags instrument

| | Non-Linear Model | | |
|---|---|---|---|
| Dependent Variable (Units of Steel Production) | All<br>(1) | BOF<br>(2) | EAF<br>(3) |
| Expected Coking Coal Price | -0.642*** | -0.768*** | -0.556*** |
| | (0.152) | (0.146) | (0.159) |
| Pre-Sample Mean | 0.654*** | 0.673*** | 0.623*** |
| | (0.046) | (0.066) | (0.040) |
| Year Trend | Yes | Yes | Yes |
| Overidentification Test | | | |
| Hansen's J chi2 | 6.91 | 6.92 | 7.26 |
| p-value | 0.1408 | 0.1404 | 0.1227 |
| Observations | 551 | 276 | 275 |
| Countries | 19 | 19 | 19 |

Notes: The non-linear model uses GMM. The first five lags of the expected coking coal price are used as instruments. The models include a time trend. Dependent variable is normalized at each time period. Independent variables are included in logarithmic form. Clusters are set at country level. Cluster-robust standard errors in parentheses. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

Table 4 presents the estimation with the five lags of the expected coal price used as instruments to explain the variation of today's prices. Results do not vary significantly. In facts, the difference of the effects of coal price on active steel units of BOF compared to EAF is even bigger in this case. Looking at the p-value of the Hansen's J chi2, we cannot reject the null hypothesis at 10% level. This validate our instruments, as they are proved to be uncorrelated with the error term.

Secondly, we modify the extension of the pre-sample period. In the original specification (Table 3) we consider as pre-sample the interval (1960-1978), while the actual sample for the estimation ranges from 1979 to 2014.

Table 5: Pre-Sample Mean Estimation, pre-sample starting in 1970

| Dependent Variable (Units of Steel Production) | Non-Linear Model<br>All<br>(1) | <br>BOF<br>(2) | <br>EAF<br>(3) |
|---|---|---|---|
| Expected Coking Coal Price | -0.458*** | -0.517*** | -0.444*** |
| | (0.105) | (0.080) | (0.148) |
| Pre-Sample Mean | 0.748*** | 0.756*** | 0.716*** |
| | (0.052) | (0.052) | (0.052) |
| Year Trend | Yes | Yes | Yes |
| Observations | 715 | 356 | 359 |
| Countries | 22 | 22 | 22 |

Notes: The non-linear model uses GMM. The first lag of the expected coking coal price is used as instrument. The models include a time trend. Dependent variable is normalized at each time period. Independent variables are included in logarithmic form. Clusters are set at country level. Cluster-robust standard errors in parentheses. $^{*}$,$^{**}$ and $^{***}$ respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

To check the robustness of this specification we modify the starting date of the pre-sample, setting it to 1970 (see Table 5). Arguably, the economies under analysis have changed a lot between the '60s and the '70s. In restricting the pre-sample period, we come closer to proxy a fixed effect through the inclusion of the pre-sample mean. Results are robust to change in the pre-sample definition. Additional robustness checks are reported in Appendix B. We run the same estimation in a linear setting (see Table B1), with contemporaneous coal prices instead of expected ones (see

Table B2), using a lag-model to predict coal prices instead of the ARIMA (see Table B3), with non-logarithmic coal prices (see Table B4) and with steam coal prices instead of coking coal ones (see Table B5). Additionally, for completeness we present results with alternative estimators (see Table B6), namely OLS, fixed-effect and first-difference, which are proved to be inconsistent in a setting like ours.

## 6. Simulations

We now run a simulation where we quantify the effect of implementing a carbon tax or 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 $t$, would have raised the price of carbon by an additional $\$31/tCO^2$, which 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 $\$31/tCO^2$ into a coal price increase by assuming that a ton of coal emits 2.457 tons of CO2 equivalent (Trust, 2008). We therefore raise the price of coal in regulated countries by about \$ 76 per ton.

We define three scenarios, according to the geographical coverage of the policy. In the business as usual scenario, the policy is implemented nowhere. In the all countries scenario, this policy is implemented in the 22 countries of our sample. We furthermore develop one additional scenario in which the carbon market or tax is applied only in European countries  this scenario corresponds to the one where the steel industry would be strictly regulated under the EU ETS, in which carbon emissions would be priced at \$ 31 per ton. Using our empirical model, we compute the number of units that would have operated in country i over the sample period (1978-2014) under all three scenarios. We generate predictions on the number of active units of steel-making production in each country and each scenario, and on the number of units that use the EAF technology. We then look at the relative market shares of steel units present in Europe, North America and Asia. Demand is assumed to be completely elastic to supply shocks. Results are reported in Table 6.

Table 6: Simulations: implementation of a carbon tax in different regions of the world

| *Scenario* | *Business as usual* | | *All regions* | | *Europe* | |
|---|---|---|---|---|---|---|
| | Shr Units | Shr EAF | Shr Units | Shr EAF | Shr Units | Shr EAF |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| North America | 24.82% | 76.50% | 26.47% | 79.50% | 25.69% | 76.50% |
| Europe | 24.35% | 63.08% | 31.53% | 65.14% | 21.69% | 65.14% |
| Asia | 49.49% | 50.48% | 41.07% | 56.55% | 51.23% | 50.48% |
| Other regions | 1.34% | 44.67% | 0.93% | 45.16% | 1.38% | 44.67% |

Notes: The simulations are run for the case of the implementation of a carbon scheme with an optimal price of carbon of $\$31/tCO^2$. 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. 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.

In the business as usual scenario, 24.8% of plants are in North America, 24.4% are in Europe, 49.5% are in Asia, and 1.34% in other regions of the world. EAF plants represent 76.5% of North American plants, 63.1% of European plants, 50.5% of Asian plants, and 44.67% of other regions' plants. In the all countries scenario, Asian countries significantly lose market share (minus 8.4 percentage points), mostly in favour of European countries (plus 7.2 percentage points). Higher coal prices also lead to an improvement of production processes everywhere, in Asia particularly where the share of EAF plants would increase by 6.1 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. In the scenario where the coal price increase only affects European countries, the share of steel units present in Europe goes down to 21.7%. This is an 11% reduction in market share. The share of EAF units would increase by 3.2% (from 63.1% to 65.1%) in Europe.

These simulations are informative about the upcoming difficulties in finding common agreements on carbon markets across the globe. Our figures suggest that 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 taxed worldwide because they specialised more in BOF technologies. Finally, cross-country relocation effects appear stronger than within country changes in steel-making technologies.

## 7. Conclusions

The Paris Agreement, in 2015, has proven 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 CO2 in the atmosphere. Given the availability of two perfectly substitutable steel-making technologies, the interest lies on the possibility, thorugh environmental policies, to shift steel production from BOF to EAF, making it less carbon intensive. Multiple studies have analyzed the steel sector dynamics focusing on this possible technological shift. Indeed, we have observed across the years an increase share of adoption for EAF compared to BOF. Nevertheless, countries largerly endowed with cheap fossil fuel remain largerly dependent on dirty production of steel.

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. With a pre-sample mean GMM estimator which allows us to account for the simultaneity problem between steel plants location and input prices, we find that on average an increase of 1% in the expected price of coal reduces the number of steel-making units active in one country by 0.55%. This effect differs across types of production technologies: BOF units are hit on average more than EAF ones (0.67% reduction compared to only 0.45%), implying an overall reduction in the energy intensity of steel production of 0.6%. With our analysis, we find evidences of the induced innovation hypothesis showing that through a carbon tax we may achieve a shift of the steel industry from BOF to EAF.

We complement the empirical study with a simulation exercise which test the efficacy of different green coalitions in undertaking a combined action to implement a carbon tax. When we simulate the effect of regional increases in prices, we find that European firms would lose competitiveness if they were to unilaterally set a binding carbon price on their firms. However, a uniform increase of coal prices across the globe is also found to have an impact on the location of steel plants. Asian firms would be more severely touched because Asian countries are the ones that are the most dependent on BOF technologies. From a multilateral perspective, allowing for differentiated carbon prices across the globe could be a useful tool to encourage countries to participate in a global carbon market. If well balanced and coordinated, differentiated carbon prices could mitigate the risks of relocation for all actors, and therefore increase the political acceptance of a multi-country regulation of GHG emissions.

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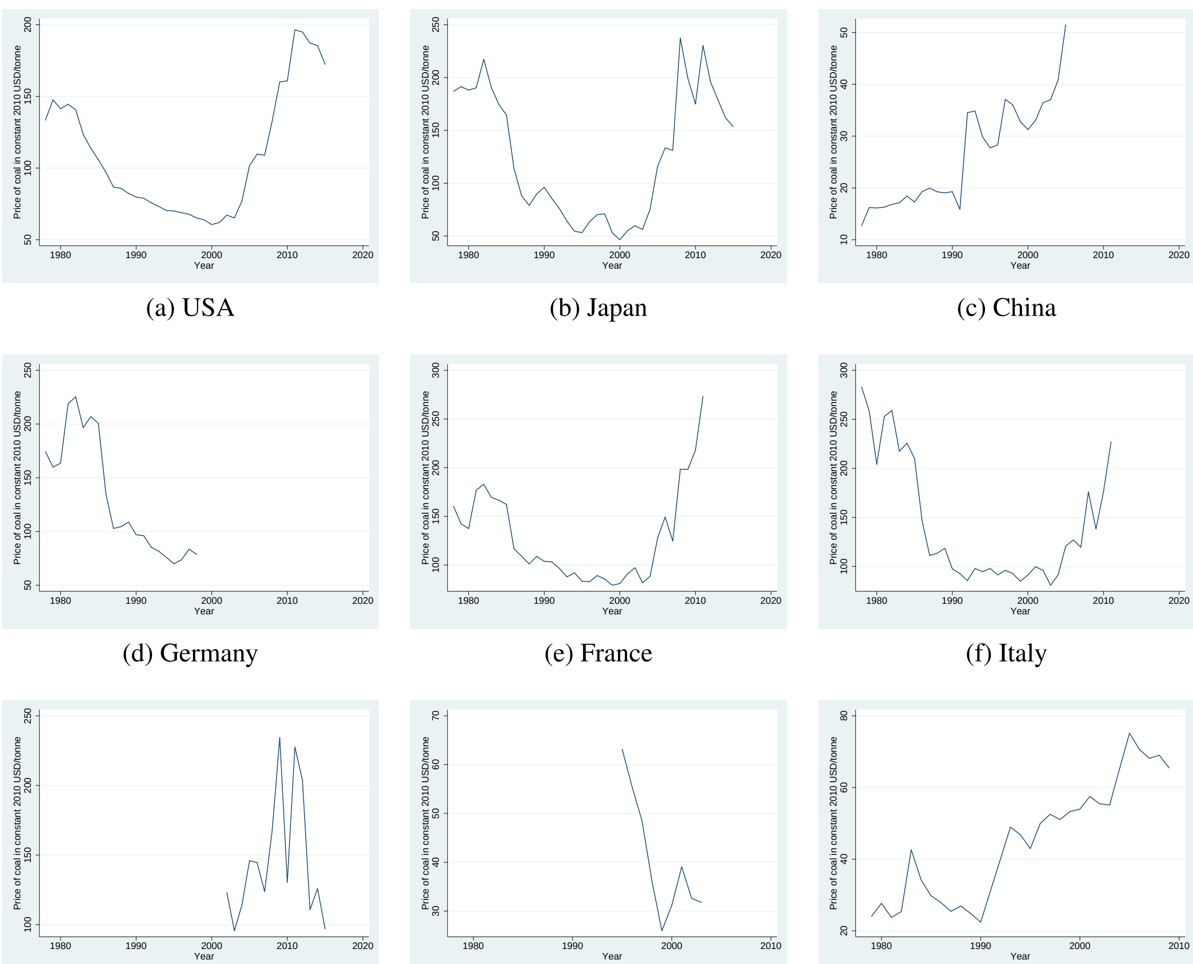
# Appendices

## A. Building the dataset

As underlined in Section 3 we employ different data sources to build a stream of coal prices expressed in constant 2010 USD/tonne. Data from IEA and from multiple Chinese statistics are extracted in national currency/tonne.
We apply the following formula to convert them in constant 2010 USD/tonne:

$$P^{cons2010} = \frac{P_t^{LC}}{deflator_t^{GDP}} \frac{deflator_{2010}^{GDP}}{r_{2010}^{x}}, \tag{1}$$

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.



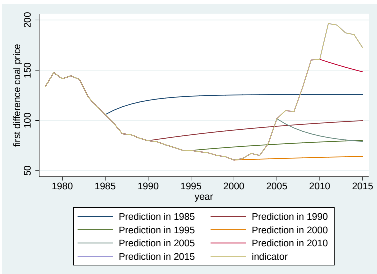

(a) USA (b) Japan (c) China

(d) Germany (e) France (f) Italy

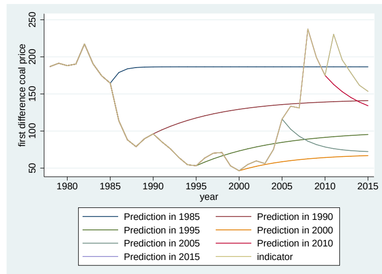
(g) Chile (h) Russia (i) India

Figure 3: Evolution of coking ore prices, country decomposition.

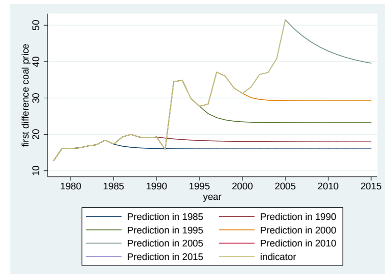
Figure 3 features the evolution of coking coal prices for the bigger steel producers in our sample. Using the actual price of coal, we can predict the expected price, based on the ARIMA model introduced in Section 4.



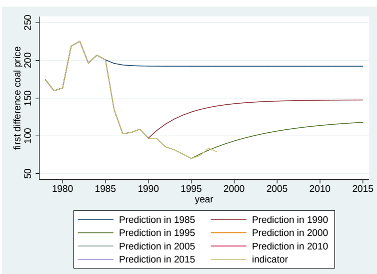

(a) USA



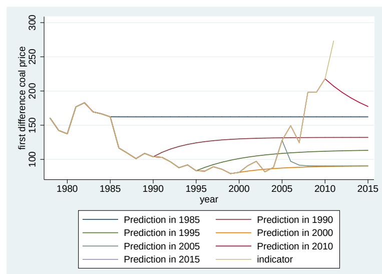

(b) Japan



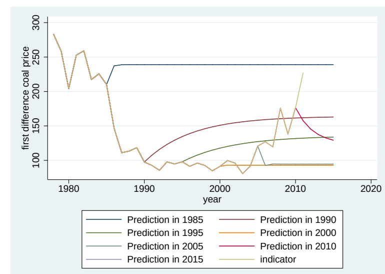

(c) China



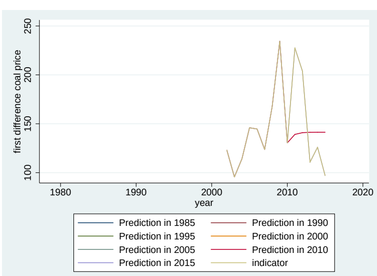

(d) Germany



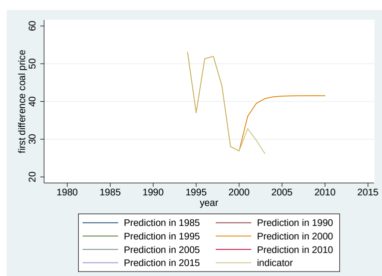

(e) France



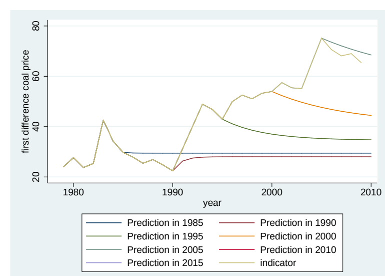

(f) United Kingdom




(g) Brazil




(h) Russia




(i) India

Figure 4: Expected coking coal prices as predicted with the ARIMA model.

Figure 4 shows, for a selected group of countries in our dataset, the expectations on coking coal prices made through the ARIMA (1,0,0) model in Equation 1. Predictions are reported for specific years (namely 1990, 1995, 2000, 2005, 2010 and 2015), but they are available for each year of the analysis.

## B. Other Robustness Checks

We report here other robustness checks to confirm the validity of our findings.

Table B1: Pre-Sample Mean Estimation, Linear Model

| Dependent Variable (Units of Steel Production) | Linear Model - IV (2SLS) All (1) | BOF (2) | EAF (3) |
|---|---|---|---|
| Expected Coking Coal Price | -0.026** | -0.025** | -0.025** |
| | (0.011) | (0.012) | (0.011) |
| Pre-Sample Mean | 0.468*** | 0.524*** | 0.457*** |
| | (0.025) | (0.089) | (0.018) |
| Year Dummy | Yes | Yes | Yes |
| Weak Identification Test | | | |
| Kleibergen-Paap rk Wald F statistic | 6777.68 | 5799.90 | 6364.05 |
| Stock-Yogo critical value (maximum bias 10%) | 16.38 | 16.38 | 16.38 |
| Observations | 723 | 364 | 359 |
| Countries | 22 | 22 | 22 |

Notes: The linear model uses the IV 2SLS. The first lag of the expected coking coal price is used as instrument. The models include a time dummy. Dependent variable is normalized at each time period. Independent variables are included in logarithmic form. Clusters are set at country level. Cluster-robust standard errors in parentheses. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

The linear version of the pre-sample estimator, shown in Table B1, uses an IV-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 allows to compute statistical tests and verify the validity of the instrument. We report the Weak Identification Test. The relevance of the instrument is suggested by the high Kleibergen-Paap rk Wald F statistics.

Table B2: Pre-Sample Mean Estimation, Contemporaneous Coking Coal Prices

| Dependent Variable (Units of Steel Production) | Non-Linear Model All (1) | BOF (2) | EAF (3) |
|---|---|---|---|
| Coking Coal Price | -0.457*** | -0.546*** | -0.389*** |
| | (0.137) | (0.160) | (0.127) |
| Pre-Sample Mean | 0.697*** | 0.747*** | 0.658*** |
| | (0.035) | (0.063) | (0.038) |
| Year Trend | Yes | Yes | Yes |
| Observations | 865 | 429 | 436 |
| Countries | 22 | 22 | 22 |

Notes: The non-linear uses GMM. The first lag of the actual coking coal price is used as instrument. The models include a time trend. Dependent variable is normalized at each time period. Independent variables are included in logarithmic form. Clusters are set at country level. Cluster-robust standard errors in parentheses. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

Table B2 reports the estimation results obtained using the actual coal prices instead of expected ones as the main independent variable. Coefficients have lower intensity here if compared to the main specification (Table 3). This can be attributed to the fact that agents adjust their production decisions based on expected rather than actual input prices. This holds even more in a rigid sector like steel, where investments in new plants are stiff and difficult to reconvert in short horizons.

Table B3: Pre-Sample Mean Estimation, Lag Models of Coking Coal Prices

| | (1) Coeff | Se | (2) Coeff | Se | (3) Coeff | Se | (4) Coeff | Se | (5) Coeff | Se |
|---|---|---|---|---|---|---|---|---|---|---|
| All | -0.481*** | 0.141 | -0.497*** | 0.143 | -0.521*** | 0.146 | -0.541*** | 0.145 | -0.569*** | 0.145 |
| BOF | -0.573*** | 0.162 | -0.599*** | 0.164 | -0.635*** | 0.166 | -0.663*** | 0.164 | -0.702*** | 0.164 |
| EAF | -0.411*** | 0.131 | -0.420*** | 0.133 | -0.436*** | 0.138 | -0.450*** | 0.139 | -0.471*** | 0.141 |

Notes: Only coefficients associated with expected coking coal price are presented, along with their standard error. The models include year dummies. Standard errors are clustered at country level. Independent variables are included in logarithmic form. Instrument used in columns (1)-(5) is the first lag of the dependent variable. *,** and *** respectively denote significance at 10%, 5% and 1% levels.

Table B3 features the pre-sample mean estimators in a lag model setting. Different combinations of previous coal prices are included as the main independent variable $x_{i,t}$:

$$x_{i,t} = \sum_{j=1}^{q} (\frac{1}{q}) p_{i,t-j}. \tag{2}$$

Agents form their belief about future coal prices through a linear combination of past prices observed over the last $q$ years. $q$ ranges from 1 in column (1) to 5 in column (5). Results are robust to different ways of molding expectations. Whenever agents add more past information to form their belief, results tend to converge to what we find in the basic specification in Table 3 where expected prices are estimated through the ARIMA(1,0,0) model.

Table B4: Pre-Sample Mean Estimation, Non-logarithmic Coking Coal Prices

| Dependent Variable (Units of Steel Production) | Non-Linear Model All (1) | BOF (2) | EAF (3) |
|---|---|---|---|
| Coking Coal Price | -0.0056** | -0.0072** | -0.0046* |
| | (0.0028) | (0.0033) | (0.0025) |
| Pre-Sample Mean | 0.657*** | 0.706*** | 0.618*** |
| | (0.045) | (0.084) | (0.044) |
| Year Trend | Yes | Yes | Yes |
| Observations | 715 | 356 | 359 |
| Countries | 22 | 22 | 22 |

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

Table B4 presents the esimation where the expected coal prices are included in normal values instead of the logarithmic form. We have now a log-level regression instead of a log-log one. Therefore, the magnitude of the estimated betas is 100 times smaller, but the overall effect remains unchanged: we still find a bigger impact of the price of coal on BOF rather than EAF.

Table B5: Pre-Sample Mean Estimation, Steam Coal Prices

| Dependent Variable (Units of Steel Production) | Non-Linear Model | | |
|---|---|---|---|
| | All | BOF | EAF |
| | (1) | (2) | (3) |
| Steam Coal Price | -0.515* | -0.564 | -0.476** |
| | (0.280) | (0.343) | (0.234) |
| Pre-Sample Mean | 0.621*** | 0.664*** | 0.598*** |
| | (0.060) | (0.099) | (0.057) |
| Year Trend | Yes | Yes | Yes |
| Observations | 667 | 319 | 348 |
| Countries | 20 | 20 | 20 |

Notes: The non-linear uses GMM. The first lag of the expected steam coal price is used as instrument. The models include a time trend. Dependent variable is normalized at each time period. Independent variables are included in logarithmic form. Clusters are set at country level. Cluster-robust standard errors in parentheses. *,** and *** respectively denote significance at 10%, 5% and 1% levels. Coefficient of constant has not been reproduced.

In Table B5, we include steam coal prices instead of coking coal ones. As this type of coal is only used in EAF processes, we find a significative negative effect only for the EAF estimation, but not for the BOF one. Even if not significant the BOF coefficient is negative and bigger than the EAF one.

Table B6: Other Estimation Methods

| | OLS (1) | | FE (2) | | FD (3) | |
|---|---|---|---|---|---|---|
| | Coeff | Se | Coeff | Se | Coeff | Se |
| All | -0.032*** | 0.011 | 0.014 | 0.009 | 0.002 | 0.001 |
| BOF | -0.031** | 0.012 | 0.014 | 0.010 | 0.003 | 0.002 |
| EAF | -0.033*** | 0.011 | 0.013 | 0.009 | 0.002 | 0.002 |

Notes: Only the coefficients associated with expected coking coal price are presented, along with their standard error. The models include year dummies. Standard errors are clustered at country level. 'OLS' makes use of a general pooled OLS procedure for the estimation. 'FE' is the fixed-effect estimator. 'FD' is the first-difference estimator. Independent variables are included in logarithmic form. Instrument used in columns (3) is the first lag of the dependent variable ("expected price of coking coal"). *,** and *** respectively denote significance at 10%, 5% and 1% levels.

In Table B6 we report the results from other methods of estimation. We, respectively, take into consideration: pooled ordinary least squares (OLS), fixed-effect (FE) and first-difference (FD) estimators. The variables included in the regressions are the same as our main specification: number of units of steel production as dependent variable, price of coking coal as independent variable. Year dummies are included in all models. The first lag of the endogenous variable (coking coal price) is used as instrument for the endogenous variable itself only in the FD estimation, as OLS and FE does not support pre-determined variables as instruments. Pooled OLS and FE are both inconsistent because they don't account for simultaneity between the output (production of steel) and the input (price of coal). FD is subject to small sample bias and therefore its estimates should be considered incorrect.

## C. Simulations

Table C1: Simulations: implementation of a carbon tax in different regions of the world, top-10 steel-making countries

| *Scenario* | *Business as usual* | | *All regions* | | *Europe* | |
|---|---|---|---|---|---|---|
| | Shr Units | Shr EAF | Shr Units | Shr EAF | Shr Units | Shr EAF |
| China | 26.05% | 47.21% | 20.83% | 53.94% | 26.97% | 47.21% |
| USA | 22.50% | 79.16% | 23.41% | 83.58% | 23.29% | 79.16% |
| Russia | 7.40% | 73.17% | 5.47% | 86.42% | 7.66% | 73.17% |
| India | 5.69% | 58.15% | 4.07% | 68.33% | 5.89% | 58.15% |
| Germany | 5.43% | 53.17% | 7.35% | 49.22% | 5.06% | 49.22% |
| Turkey | 3.42% | 82.00% | 4.99% | 83.46% | 3.43% | 83.46% |
| Spain | 3.13% | 82.31% | 6.21% | 83.06% | 4.27% | 83.06% |
| Italy | 2.43% | 59.38% | 2.87% | 62.65% | 1.97% | 62.65% |
| Canada | 2.32% | 50.74% | 3.06% | 48.22% | 2.41% | 50.74% |
| France | 2.06% | 56.84% | 2.30% | 62.60% | 1.58% | 62.60% |

Notes: The simulations are run for the case of the implementation of a carbon scheme with an optimal price of carbon of $\$31/tCO^2$. Share of active units is calculated as the number of active steel-making units in a country over the total number of active units in the rest of the world. Share of EAF is calculated as the proportion of EAF units over the total number of steel-making units in a country. 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.

Table C1 reports the result of the simulation disaggregated by country, for the 10 bigger producers of steel. In this table, we can observe how some countries could benefit more from the plants relocation than others (e.g. Spain registers an increase in the share of units of 3.08 percentage points). This can be attributed to initial differences in relative coal prices in each country.[19] There is a minority of countries (Germany and Canada)[20] for which the implementation of the carbon tax actually discourages more EAF rather than BOF

[19]When an uniform carbon tax is raised all over the world, countries with low initial energy prices would register a big negative effect due to relocation, while those with high initial energy prices will instead register an overall positive and big effect. For example, Spain has on average higher coal prices with respect to Italy. They both register a positive effect on the share of units following the imposition of the same carbon tax, but the effect is bigger for Spain rather than Italy.

[20]If we look at the total sample, the full list of countries registering a decrease of the share of EAF when the carbon tax is implemented is: Chile, Belgium, Germany, Finalnd, Norway, Poland, Sweden and Canada

production. This may be due to idiosyncratic characteristics which are accounted for in the error term. These countries should consider not to raise at all the carbon tax, as they may experience a direct pollution haven following from the increase in production share and the decrease in EAF share.