Does climate change pose a risk to competitiveness? - Global firm level evidence

Antoine Dechezlepretre, Stefania Lovo, Ralf Martin, Misato Sato*

May 30, 2017

Abstract

An important concern is the risk to international competitiveness of unilateral climate policy. We explore this risk by looking at past differences in energy prices between countries. Specifically we explore how firm level employment is affected by energy price disparities using a global firm level panel database (ORBIS). We find that estimates are highly sensitive to specific model assumptions. However, in our most general conventional regression model we do not find any evidence of a negative impact of energy prices on firm level employment. However, we also develop a new kind of estimator - the Worst case scenario estimator (WOCASCE) - that systematically tries to find the most dramatic impact of energy price gaps on firm level employment from a wide range of possible model specificaitons. This leads to moderately negative energy price elasticities ranging from -0.17 for the Chemical sector to -0.09 for the Iron&Steel sector; i.e. a 10% increase of energy prices in Chemicals relative to competitors would lead to a 1.7% reduction of employment in the worst case.

Keywords: Climate Policy, Competitiveness, Energy prices, Employment
JEL: J23, Q50

1 Introduction

Much of climate policy to date is unilateral in nature. This implies that some countries - or groups of countries such as the EU - have imposed more stringent climate policy measures than others. This raises the concern that such policies could undermine the competiveness of countries with more stringent policy. What is worse, if emissions "leak" to countries with less stringent policies the cost of reduced competitiveness would arise without any benefit in terms of reduced risk for the climate.Even in regions with more stringent climate policy, such as the EU the stringency of current interventions is still far below the levels many believe are required to trigger the necessary changes; e.g. the EUETS carbon price has consistently been below expected levels.[1] Concerns about competitiveness risk are primarily associated with calls for more stringent future policy rather than existing policies that are not particularly stringent. Hence, in order to assess the validity of such concerns we cannot rely on existing climate policy. However, in most industries climate policy

*Grantham Institute and Centre for Economic Performance, London School of Economics and Imperial College London

[1] Exisitng literature on negative competitiveness effects of speicific policies such as the ETS could not establish any strong evidence.

such as carbon pricing would primarily affect firms through its effect on energy prices. While there are common factors such as global oil and gas prices that affect energy prices everywhere, there has been considerable country specific heterogeneity for reasons such as energy taxes or limited integration of markets because of transport costs or infrastructure bottlenecks. Hence we attempt to make inferences about the competitiveness effects of climate policy by looking at past country and sector level differences in energy prices and firms' performance. There is no commonly accepted definition of competitiveness. We operationalise the idea by looking at employment of affected firms. Employment is also the most likely concern for policy makers fearing re-election when enacting climate policies. Hence, we focus on this area first and defer other potential outcomes to future research.

We analyse this issue using a global firm level database (ORBIS) covering eight energy intensive sectors located in 42 countries combined with historical data on energy prices and wages at the sector level for the period 2000-2010. This allows us to highlight heterogeneities at any level of aggregation and also exploit sector level heterogeneities to identify competitiveness risk. While our focus is on the competitiveness of European firms, we compare their performance to firms in all the 42 countries for which data are available.

Climate policies typically put upward pressure on energy prices and policy makers are concerned about the negative effects this might have on business performance. Our prior is that the price effect is negative and a pessimistic estimate can be defined by the most negative impact when in doubt. To obtain such a lower bound estimate we develop a new estimator - the Worst Case Scenario (WOCASCE) estimator - that systematically searches for extreme responses while meeting a number of plausibility constraints. We expect the impact of a change in energy prices to produce more dramatic effects when it affects asymmetrically firms competing for the same market. Because actual competitors cannot be observed for all firms, the WOCASCE estimator allows us to repeatedly match each firm with a random firm within the same sector but located in another country in search for pairs that are most sensitive to variations in energy prices.

The results show that even the worst case scenario effects are moderate; a 1% increase in energy prices lead to a decrease in employment in the range of 0.05% to 0.15%. The only exceptions are the Coke and refined petroleum products and the Pharmaceutical sectors.For the Coke and refined petroleum products sector, our findings indicate that, for some firms where an increase in energy prices produces a notable cost pressures from competitors, a 1% increase in energy prices could induce a 0.7% decrease in employment. This is not surprising as the share of energy costs in total production costs is extremely high for this sector. In contrast, it is less intuitive why employment effects are high in Pharmaceuticals where energy costs are low. This, however, is little informative of the potential impact of an increase in carbon prices within the EU. First, distance is an important determinant of the market area for a firm. Therefore, we expect European firms to compete mostly between each other rather than with farther non-EU firms. Second, although the impact of the EU-ETS will differ across firms depending on the level of free allocation received, the main source of concern will likely be the carbon price gap with non-EU competitors. We, therefore, provide a second scenario where we match firms in EU-ETS countries with non-European firms in order to gauge a better sense of the potential impact of an increase in European carbon prices.

The results show substantial lower impacts when potential competitors are not allowed to be in EU countries. Again the Coke and refined petroleum products and the Pharmaceutical sectors show the most negative impacts but now in the range of -0.3% to -0.35%. Future increases in European carbon prices are, therefore, expected to have only marginal impacts on employment of European firms even in the most pessimist situation where energy costs produce great cost pressure from foreign competitors.

2 Environmental policies and firm employment

In political debates, the employment effects or rising energy price or environmental regulation are typically characterized by fear of potential job losses due to increased compliance costs and hence production costs. However, employment impacts at the economy level are a priori undetermined. Pollution abatement activities might require labour input, either directly at regulated plants or higher up the technology supply chain. Jobs lost at regulated entities could be partially offset by hires at non- or less-regulated entities. Thus, the net effect of environmental regulation on short run employment depends on the relative labour intensity of polluting and non-polluting industries (Fankhauser and Stern, 2008). Moreover, while there could well be adjustment costs in the short run as workers move from polluting to cleaner sectors, in the long run, environmental regulations might simply induce a substitution between polluting and non-polluting activities.

What does the empirical evidence tell us? The existing studies on this topic evaluate the impact of the US's Clean Air Act Amendments. Kahn (1997) finds 10% lower growth rates in manufacturing employment in counties with stringent air pollution regulations compared to less regulated counties. Using the same approach and a long panel of United States plant level data (1972-1987), Greenstone (2001) finds that the Clean Air Act Amendments of the 1970s led to a loss of around 590,000 jobs in (strictly regulated) nonattainment counties relative to attainment ones (subject to more lenient regulation). This represents 3.4 percent of manufacturing employment in the United States and less than 0.5 percent of total employment. Part of this lost activity in nonattainment counties may have moved to attainment counties, so that the net national effect on employment is likely to be smaller. Moreover, many of these job losses are unlikely to be permanent as laid-off workers ultimately find other jobs, so that "the appropriate measure of regulatory costs to the workforce should not be characterized by jobs lost but by any transitional costs associated with reallocating production or workers" (Walker, 2011). Walker (2013) estimates the transitional costs from the Clean Air Act Amendments. He finds that the average worker in a regulated sector experienced a total earnings loss equivalent to 20 percent of their pre-regulatory earnings. Almost all of the estimated earnings losses are driven by unemployment. Overall, the total forgone wage bill associated with this regulation-induced sectoral shift in production, estimated to be 5.4 billion USD (in 1990 dollars), is two orders of magnitude below most estimates of the health benefits of the 1990 Clean Air Act Amendments.

A range of studies, including some that also focus on the US Clean Air Act, do not find evidence for such negative impacts of environmental regulation on employment. Morgenstern et al. (2002) use pollution abatement operating costs as a proxy for the stringency of environmental regulation and find that higher environmental spending generally does not cause a statistically significant change in employment. There are even statistically significant and positive effects in two industries, but total number of affected jobs remains quite small. These estimates suggest that, at most, environmental regulation accounted for 2 percent of the observed decline in employment from 1984 to 1994. Belova et al. (2013) also use pollution abatement operating costs as a measure of environmental regulatory stringency and find no evidence of negative employment effects from environmental regulations. Berman and Bui (2001a) compare petroleum refineries in the Los Angeles area, subject to some of the strictest air pollution regulations in the United States, to all other refineries in the country. They find no evidence that environmental regulation decreased labour demand, even allowing for induced plant exit and dissuaded plant entry. They actually find weak evidence that regulations may have resulted in a small net increase in employment, possibly because more labour is required for pollution control activities. The lower bound of their estimates implies fewer than 3,500 jobs lost due to regulation over 12 years, a number equivalent to the estimated deaths every year from pollution in counties not complying with national standards in the mid-1980s. Cole and Elliott

(2007) estimate a similar model to Berman and Bui (2001b) but use data for 1999-2003 on 27 industries in the United Kingdom. and found no evidence that environmental regulations reduce employment. Ferris et al. (2014) examine the employment effects of Phase I of the Title IV cap-and-trade program for SO2 emissions implemented under the 1990 Clean Air Act Amendments (CAAAs). Using a panel data set that includes 61 regulated and 109 unregulated plants, they examine the impact of environmental regulation on employment using propensity score matching followed by difference-in-differences estimation. They find little evidence that power plants subject to Phase I of the SO2 trading program experienced significant decreases in employment relative to non- Phase I power plants. employment is significantly lower in Phase I plants relative to non-Phase I plants in the first year of compliance but not in subsequent years. However, this results is not robust to aggregating the data at the utility level, suggesting firms might be simply relocating employees between plants. A few recent studies have looked at the impact of energy prices on employment, making it possible to examine the impact that a hypothetical carbon tax would have. Deschenes (2011) finds that employment rates are weakly related to electricity prices, a 1 percent increase in electricity prices leading to a change in full-time equivalent employment ranging from -0.16 percent to -0.10 percent. Aldy and Pizer (2011) also exploit the United States state-level variation in industry energy prices between 1990 and 2009 to estimate the price-employment relationship. They simulate the impact of a 15 USD per ton carbon tax corresponding to an 8 percent increase in electricity prices in the United States relative to the rest of the world and find that this would cut employment by 0.2 percent. Kahn and Mansur (2013) exploit variation in energy prices and in environmental regulation among adjacent counties and use a relatively long panel (1998-2009). They find evidence that energy intensive sectors locate in low electricity-price areas and that polluting sectors seek out low regulation areas, reducing employment in high regulation areas. The effects are modest for the typical manufacturing industry, but the most electricity-intensive industry, primary metals, has an implied price elasticity of employment of -1.65. The effect of a 15 USD per ton carbon tax would vary according to the carbon intensity of electricity production and to the energy intensity of the industry across states. For example employment would fall by 3.8 percent in Ohio compared to a mere 0.3 percent in California.

A number of recent studies have examined the impact of the EU ETS on employment, and there is no evidence that the EU ETS might have negatively affected the economic performance of regulated firms Martin et al. (2014). Anger and Oberndorfer (2008) compare EU ETS firms with each other, using the allocation factor (the ratio between allowances allocated for free and verified emissions) as an indicator of the stringency of the regulation at the firm level. They find no evidence of an impact of the allocation of EU emissions allowances on firm employment. Simiarly, Commins et al. (2011) do not find a statistically significant effect of the EU ETS on employment, however as mentioned above their definition of EU ETS regulation is at the sector level, and hence all small unregulated installations are wrongly considered as treated. Abrell et al. (2011) use a better methodology. They estimate the impact of the EU ETS on regulated firms by matching each EU ETS firm with a similar firm - based on observable firm characteristics - in a non-EU ETS sector. In the period between 2004 and 2008, they find a statistically significant, slight decrease in employment at EU ETS firms of 0.9%. This result is driven by the non-metallic minerals sector. However, as the authors acknowledge, taking control firms only from non-regulated sectors is problematic because of the possible non-random selection of which sectors were regulated under the EU ETS. For this reason, the study is likely to suffer from selection bias at the sector level. Chan et al. (2013) estimate the impact of the EU ETS on economic outcomes by comparing firms regulated under the EU ETS with unregulated firms in three sectors: cement, steel and power production. They cannot determine the sign of the effect with confidence for either of the three sectors analysed.

To sum-up, the most rigorous studies that use installation or county level data from the United

States and long panels have found negative effects on employment in pollution intensive sectors from environmental regulations, as measured by Clean Air Act nonattainment status or by the level of energy prices. This suggests that, in the United States at least, differences in environmental regulations between states or counties have led to small negative effects on employment in polluting sectors. However, the social costs of job losses appear much smaller than the health benefits from environmental regulations and typically represent less than 10 percent of other social costs of regulations, so that including job losses in cost-benefit analyses of environmental regulations is unlikely to change their conclusions (Bartik, 2013). Comparing the results by Aldy and Pizer (2011) with those of Kahn and Mansur (2013), it also appears that employment effects are larger within national boundaries (where relocation barriers are lower) than across countries and that the net effect of environmental regulation is much smaller than the effect on strictly-regulated firms and regions. Many studies looking mostly at the US but also at Europe in the context of the EU ETS have found no effect of environmental regulations, suggesting that the impacts of environmental regulations differ across industries and countries.

3 Empirical specification

In this section we discuss the econometric models used to estimate the impact of energy price changes on employment.

3.1 Baseline specification

Our baseline estimation is based on the following reduced-form model:

$$y_{it} = \rho y_{it-1} + \beta_{ps(i)} p_{it-1} + \beta_{ws(i)} w_{it-1} + \beta_x X_{it} + \epsilon_{it}, \tag{1}$$

where y_{it} is log employment of firm i time t, p_{it} is an index of (log) energy prices, w_{it} is the log of wages and X_{it} are various further control variables. Both, our energy price and our wage variable vary at the sectoral country level. Sectoral country level wage data are available from the ILO. We construct the energy price index on the basis of country level energy price data but with sector specific weights as we describe in more detail below. We experiment with a range variables in in the control vector X_{it}. Our most general specification includes sector $\times$ year and country $\times$ year effects. In addition we assume for the error term that:

$$\epsilon_{it} = \alpha_i + \eta_{it}$$

where we allow α_i to be correlated with the other explanatory variables and estimate the model in first differences to wipe out time invariant omitted variables. We deal with the endogeneity of the lag dependent variable by using the second lag as instrument. Note that we allow both the price and wage coefficients - $\beta_{ps(i)}$ and $\beta_{ws(i)}$ to vary at the sectoral level s.

3.2 Worse case scenario estimator (WOCASCE)

While our baseline model is able to control for a wide range of potential factors that might cause endogeneity concern might remain that not everything has been addressed. Suppose the error term contains an additional factor a_{it} that is correlated with the explanatory variables of interest:

$$\epsilon_{it} = a_{it} + \alpha_i + \eta_{it}$$

If we can find a "control" firm $j(i)$ so that the difference a_{it} - $v_{ij(i)t} = a_{it} - a_{j(i)t}$ - becomes iid we can obtain unbiased estimates by estimating the model above in differences relative to the control firm:

$$y_{it} - y_{j(i)t} = \beta_{ps(i)} \left(p_{it-1} - p_{j(i)t-1}\right) + \beta_{ws(i)} \left(w_{it-1} - w_{j(i)t-1}\right)$$

$$+\gamma \Delta Z'_{it} + \alpha_i - \alpha_{j(i)} + \nu_{ij(i)t}$$

where $\Delta Z_{it} = \left[y_{it-1} - y_{j(i)t-1}, X_{it-1} - X_{j(i)t}\right]$ and $\gamma = [\rho, \beta_x]$. The challenge is of course to find such control firms j or rather the right mapping $j(i)$. If we have already included all observable characteristics - e.g. sector etc - in our control vector there is little to guide our choice. The idea of the WOCASCE estimator is to chose a mapping that leads to the worst possible case. Hence, in our context this would be the most negative estimate for the fuel price elasticities. Formally we define the WOCASCE estimate of the energy price coefficients as the value that emerges when selecting the mapping $j(i)$ that minimises the (average across sectors) energy price coefficients:

$$\hat{\beta}_{ps}^{WOCASCE} = \min_{j(i)} \left\{ \frac{1}{N_S} \sum_{\sigma} \hat{\beta}_{p\sigma} \right\}$$

where N_S is the number of sectors. This is a rather complex optimisation problem. Suppose N_F is the number of firms in the sample. A brute force approach would cosider all $N_F^2 - N_F$ possibilities. This beomes untractable at usual sample sizes. Hence we consider instead a genetic algorithm.

3.2.1 Genetic Algorithm

Genetic algorithms are optimisation routines that mimics the process of natural selection with sexual reproduction; i.e. from a generation of various randomly selected solutions we mix the characteristics of the fitter solutions to create the next generation of solutions to converge to ever better solutions. In our current context we can define a genetic algorithm according to the following steps:

1. Draw n initial samples $g = 0$ (i.e. the first generation) by randomly matching each i with another observation j
2. Compute $\hat{\beta}_{ps\phi g}$; i.e. the least squares estimate for β for each drawn sample ϕ in generation g
3. Draw the next generation $g + 1$ by randomly combining two top performing existing samples as well as allowing for mutations at low probability i.e. draw a new random population and choose this new population with a small probality ϵ. For example, we select the two samples giving the most negative and statistically significant coefficients. However, other conditions can also be imposed[2]. We allow for 5% percent of firms to be randomly re-matched.
4. Compute $\hat{\beta}_{ps\phi g+1}$
5. If $\left|\min_{\phi}\left\{\hat{\beta}_{ps\phi g}\right\} - \min_{\phi}\left\{\hat{\beta}_{ps\phi g+1}\right\}\right|$ is small stop. If it is large carry on with another iteration (step 3)

[2]In our case, we restrict the selection to specifications that produce a negative wage coefficient, we consider this result as a way to validate the model. Since wages represent major costs for most companies, their impact on employment is expected to be negative

3.2.2 Constraints

From a theoretical point of view the energy price coefficients, which represent energy price elasticities of labour demand can be positive or negative. It depends on the substitutability between labour and energy. To the contrary, the wage coefficients cannot be plausibly positive. Moreover we would expect that wage elasticity on employment is larger than the energy price elasticity. We therefore built these constraints in the genetic algorithm; i.e. potential parents are selected only from solutions with non-positive wage coefficients that are smaller (more negative) than the energy price elasticities.

4 Data

Firm level employment data are from ORBIS maintained by Bureau Van Dijk. The sample covers 2.36 million firms in 42 countries over the period1995-2010. We currently consider only 4 of the most energy intensive manufacturing sectors(Paper, Chemicals, Iron&Steel and Minearls). However, in future versions we will have data on further sectors (17 sectors at NACE2-digit, 113 sectors at NACE3-digit). Industrial energy prices (including taxes) across 42 countries are obtained from Sato et al. (2014). In particular, we use the fixed-weight energy price Index (FEPI) constructed by combining industrial energy price by fuel type (at the country level) from the IEA Energy End-Use Prices database and fuel use data by sector and country from IEA World Energy Balances:

$$\ln(P^E_{sct}) = FEPI_{sct} = \sum_k w^k_{cs} \cdot log(P^k_{ct}), \tag{2}$$

where P^k_{ct} is the price of fuel type k in country c at time t, and w^k_{cs} is the consumption share of fuel type k in sector s. Consumption shares are based on 200X fuel use data and are kept fixed over time to capture only energy price changes that come from changes in fuel prices, and not through changes in the mix of fuel inputs that could result from technological change or other industry-specific shocks. Sector-level wages are provided by UNIDO (NDSTATS2) and National statistical offices.

5 Results

5.1 Baseline results

Table 1 reports our baseline regression results of equation 1. Column 1 reports a random effects specification, whereas in subsequent columns we report first differences results where, in column 3, the lag dependent variable is instrumented with the second lag, our preferred specification. This leads to mostly insignificant energy price coefficients. In two occasions the coefficients are positive and significant (Chemicals and Rubber and plastic sectors) suggesting possible substitution effects. Note that we can interpret these coefficients as elasticities; i.e. a 10% increase in energy price would be associated with a 0.08% increase in employment in the Chemicals sector. All wage coefficients are estimated as negative although significant only for three sectors (Pharmaceutical, Rubber and Plastic and Basic Iron and Steel).

5.2 WOCASCE results

Here we discuss the results from the WOCASCE estimator. Figure 1 shows density plots of all generations of the genetic algorithm for the case of the Paper and paper products sector and

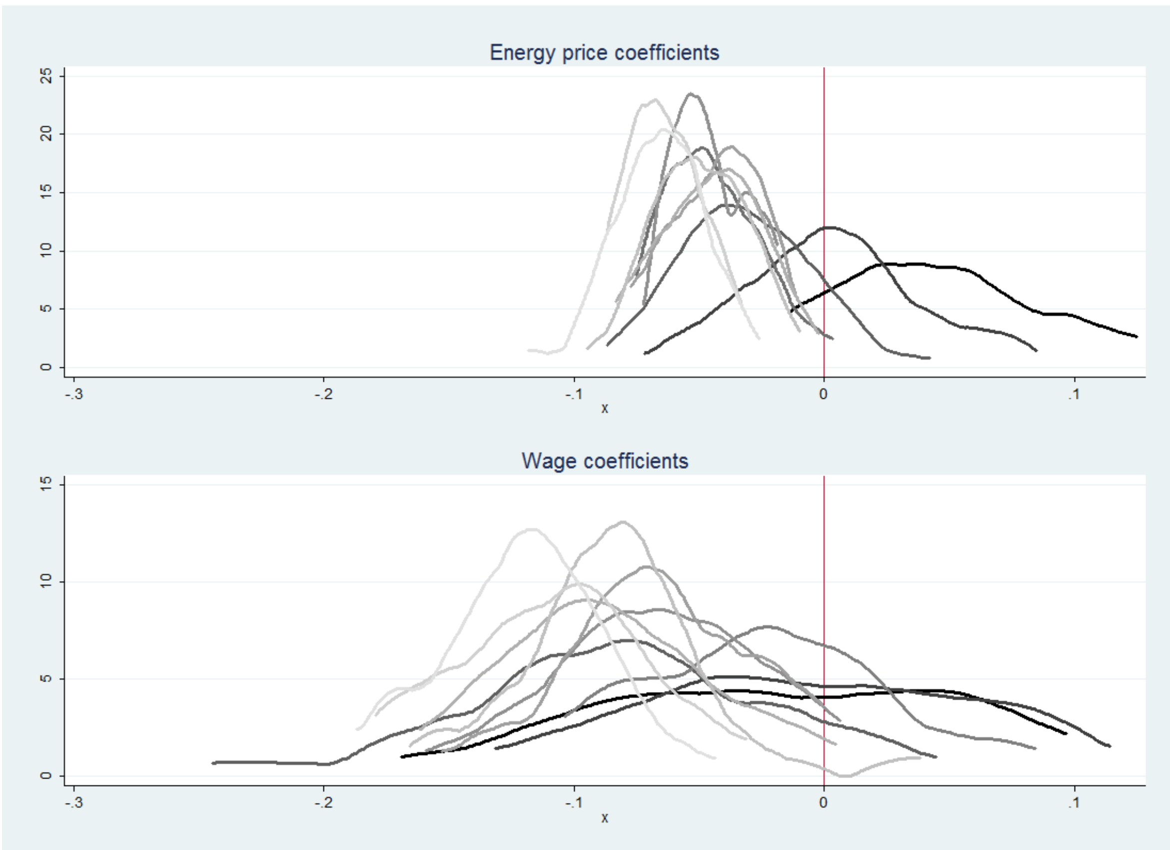
Table 1: Baseline regression results - Can't create tables in PDF

	(1) RE		(2) FD		(1) FD-IV	
Employees (log) (t-1)	0.919***	(0.001)	-0.067***	(0.005)	0.611***	(0.009)
Energy price (log) (t-1)						
Paper and paper products	-0.031***	(0.010)	0.027	(0.039)	0.045	(0.045)
Coke and refined petroleum products	-0.042*	(0.023)	0.072	(0.083)	0.050	(0.094)
Chemicals and Chemical products	-0.026***	(0.007)	0.054**	(0.027)	0.080**	(0.033)
Pharmaceutical	-0.021	(0.015)	0.131***	(0.047)	0.041	(0.054)
Rubber and Plastic	-0.002	(0.008)	0.017	(0.031)	0.100***	(0.039)
Non-metallic minerals	-0.014***	(0.005)	0.030	(0.027)	0.052	(0.033)
Basic Iron and steel	-0.004	(0.009)	0.063	(0.044)	0.036	(0.052)
Machinery	-0.010*	(0.006)	0.031	(0.025)	0.041	(0.030)
Wage (log) (t-1)						
Paper and paper products	-0.001	(0.010)	-0.114	(0.073)	-0.020	(0.098)
Coke and refined petroleum products	-0.004	(0.014)	-0.122	(0.081)	-0.082	(0.099)
Chemicals and Chemical products	-0.005	(0.010)	-0.073**	(0.036)	-0.021	(0.045)
Pharmaceutical	-0.006	(0.011)	-0.226***	(0.078)	-0.209**	(0.082)
Rubber and Plastic	-0.016	(0.010)	0.016	(0.048)	-0.147**	(0.061)
Non-metallic minerals	-0.033***	(0.009)	-0.086*	(0.051)	-0.082	(0.062)
Basic Iron and steel	-0.004	(0.011)	-0.064	(0.042)	-0.121**	(0.051)
Machinery	-0.012	(0.010)	-0.086*	(0.052)	-0.082	(0.064)
Sector-year FE	Yes		Yes		Yes	
Country-year FE	Yes		Yes		Yes	
	440168		340053		340053	
	199852		104137		104137	

Notes: Standard errors clustered at the firm level: *p<0.10, **p<0.05, ***p<0.01

considering all firms in the sample. The first generation shows that the coefficients of the energy price are on average positive while the replications produce mostly negative wage coefficients as in the baseline specification. In the second generation, instead, half of the coefficients are negative. This is re-inforced as the generations evolve. We stop when coefficients converge, which happens after 10 generations. Here the energy price coefficient is on average -0.066%. We observe that while greater responsiveness to changes in energy prices (younger generations) is associated to greater wage effects.. (this is the results of the contraint we impose for the wage coefficient to be "more negative" than the energy coefficient)

Figure 1: Worse case scenario estimator - All Generations: Paper and paper products sector



Notes: The graph shows the distribution of the energy price and wage coefficients of all generations of the genetic algorithm at the heart of the WOCASCE estimator. The fist generation is in black. Lighter shades indicate "younger" generations.

Table 2 summarizes the results for all sectors and report the average and lowest estimates for the first and last generation. Considering the results where we match all firms in the sample (colum 1 and 2) the smallest coefficients found in Pharmaceutical sector, on average -0.168. This indicates that a 10% increase in prices relative to competitors leads to a 1.68% decline in employment. For the other sectors the elasticities are smaller but of similar order of magnitude with the lowest elasticity (closest to 0) found in the rubbet and plastic sector with -0.03. Hence, compared to the baseline regression results elasticities tend to be an order of magnitude larger. Nevertheless, the numbers remain fairly low. Note that the relative ranking of sectors is also changing. According

Table 2: Impact of energy prices on employment: WOCASCE results

NACE	Sector	All firms Mean	All firms Min	EU firms Mean	EU firms Min	EU vs NON-EU Mean	EU vs NON-EU Min	MNE Mean	MNE Min
					G = 1				
17	Paper and paper products	0.046	-0.014	-0.025	-0.115	0.079	-0.006	-0.283	-0.519
19	Coke and refined petroleum products	0.057	-0.092	0.086	-0.289	0.177	-0.120	-0.084	-0.340
20	Chemicals and Chemical products	0.074	0.009	0.012	-0.067	0.042	-0.026	0.190	-0.051
21	Pharmateutical	0.030	-0.080	0.058	-0.111	0.021	-0.177	-0.255	-0.481
22	Rubber and Plastic	0.091	0.023	0.067	-0.012	0.024	-0.064	0.061	-0.185
23	Non-metallic minerals	0.055	0.011	0.068	-0.031	-0.007	-0.076	0.033	-0.219
24	Basic Iron and steel	0.031	-0.100	0.047	-0.081	0.022	-0.091	-0.270	-0.951
28	Machinery	0.038	-0.021	0.032	-0.082	-0.021	-0.098	0.008	-0.254
		G=10		G=26		G=13		G=31	
17	Paper and paper products	-0.066	-0.118	-0.198	-0.268	0.000	-0.064	-0.799	-0.947
19	Coke and refined petroleum products	-0.103	-0.156	-0.237	-0.332	-0.206	-0.316	-0.403	-0.542
20	Chemicals and Chemical products	-0.030	-0.058	-0.131	-0.166	-0.054	-0.089	-0.141	-0.262
21	Pharmateutical	-0.168	-0.221	-0.242	-0.310	-0.183	-0.274	-0.470	-0.610
22	Rubber and Plastic	-0.030	-0.067	-0.111	-0.162	-0.120	-0.177	-0.284	-0.405
23	Non-metallic minerals	-0.053	-0.092	-0.132	-0.184	-0.106	-0.142	-0.240	-0.478
24	Basic Iron and steel	-0.061	-0.121	-0.163	-0.226	-0.045	-0.123	-1.322	-1.811
28	Machinery	-0.101	-0.132	-0.137	-0.177	-0.102	-0.150	-0.299	-0.414

Notes: The table shows summary statistics of the first (top) and last (bottom) generation of the genetic algorithm at the heart of the WOCASCE estimator. Statistics refer only to iterations that satisfy the constraint of non-positivity of the wage effect.

the WOCASCE results the Pharmaceutical sector is most exposed to energy price gaps followed by Coke and refined petroleum products. This is not surprising as the share of energy costs in total production costs is extremely high for this sector. In contrast, it is less intuitive why employment effects are high in Pharmaceuticals where energy costs are low. The ranking in the linear case (random effects) saw the Coke and Refined petroleum products as most affected followed by the paper and pulp sectorThis is based on the RE because in the FD the coefficients are positive. It is difficult to claim raking as the coefficients are probabibly not statistically different.

When considering only European firms (matched with European and non-European firms), column 3 and 4, we find higher elasticities both in terms of energy prices and wages (not reported)We might not be able to explain why in theory as it could be simply due to sample selection. Similarly, the Coke and refined petroleum products and the Pharmaceutical sectors show the largest elasticities (-0.237 and 0.242 on average respectively). While focusing on European firms, these results, however, are little informative of the potential impact of an increase in carbon prices within the EU. First, distance is an important determinant of the market area for a firm. Therefore, we expect European firms to compete mostly between each other rather than with farther non-EU firms. Second, although the impact of the EU-ETS will differ across firms depending on the level of free allocation received, the main source of concern will likely be the carbon price gap with non-EU competitors. We, therefore, provide a second scenario where we match firms in EU-ETS countries with non-European firms in order to gauge a better sense of the potential impact of an increase in European carbon prices. The results, reported in column (5 and 6), show in general lower impacts when potential competitors are not allowed to be in EU countries. Again the Coke and refined petroleum products and the Pharmaceutical sectors show the most negative impacts but now in the range of -0.183% to -0.206%.

The last two columns consider only multinational corporation subsidiaries, i.e. only firms that belong to the same global ultimate owner (GUO). Multinational corporations are likely to be able to switch operation more easily from one country to another, through their network of subsidiaries, in response to international changes in energy prices. The results of the genetic alghorithm applied to this subsample of firms provide worst case scenarios estimates that allows us to gauge whether multinational corporations are associated with greater leakage. when I consider only MNE with EU and non-EU subsidiaries the GA stops because the constraints are not satisfied for two sectors

6 Conclusion

We examine the likely consequences of unilateral climate policy on the basis of historical variation in energy prices between countreis using a unique panel of global firm level data. Standard regression methods do not suggest any robustly significant negative impacts of high energy prices on employment. However, we develop a new regression approach, which we call the Worst Case Scenario Estimator. This approach does not necessarily provide an unbiased estimate of the underlying true paremeter. However, to the extent that it is biased it will be biased downward; i.e. the estimated impact of an energy price gap relative to competitors will be more negative than the true but unknown correct impact. This method suggest that in all examined sectors the energy price elasticity of employment is less than 0.2. The sector most at risk would appear to be Chemicals with a worst case elasticity of 0.165. In future work we will examine more sectors. For risk averse policy makers concerned about the potentially negative impact of Climate Change, these worst case scenario estimates could offer a cautionary guidance on how far to push forward with unilateral climate policy moves.

References

Abrell, J., A. Ndoye Faye, and G. Zachmann (2011). Assessing the impact of the EU ETS using firm level data. Technical report, Bruegel working paper.

Aldy, J. E. and W. A. Pizer (2011). The competitiveness impacts of climate change mitigation policies. Technical report, National Bureau of Economic Research.

Anger, N. and U. Oberndorfer (2008). Firm performance and employment in the EU emissions trading scheme: An empirical assessment for Germany. *Energy policy 36*(1), 12–22.

Belova, A., W. B. Gray, J. Linn, and R. D. Morgenstern (2013). Environmental regulation and industry employment: A reassessment. *US Census Bureau Center for Economic Studies Paper No. CES-WP-13-36*.

Berman, E. and L. T. Bui (2001a). Environmental regulation and labor demand: Evidence from the south coast air basin. *Journal of Public Economics 79*(2), 265–295.

Berman, E. and L. T. Bui (2001b). Environmental regulation and productivity: evidence from oil refineries. *Review of Economics and Statistics 83*(3), 498–510.

Chan, H. S. R., S. Li, and F. Zhang (2013). Firm competitiveness and the European Union emissions trading scheme. *Energy Policy 63*, 1056–1064.

Commins, N., S. Lyons, M. Schiffbauer, and R. Tol (2011). Climate policy & corporate behavior. *Energy Journal 32*(4), 51–68.

Deschenes, O. (2011). Climate policy and labor markets. In *The Design and Implementation of US Climate Policy*, pp. 37–49. University of Chicago Press.

Greenstone, M. (2001). The impacts of environmental regulations on industrial activity: Evidence from the 1970 & 1977 Clean Air Act Amendments and the census of manufactures. Technical report, National bureau of economic research.

Kahn, M. E. and E. T. Mansur (2013). Do local energy prices and regulation affect the geographic concentration of employment? *Journal of Public Economics 101*, 105–114.

Martin, R., M. Muûls, L. B. de Preux, and U. Wagner (2014). Industry compensation under relocation risk: A firm-level analysis of the EU emissions trading scheme. *The American Economic Review 104*(8), 2482–2508.

Morgenstern, R. D., W. A. Pizer, and J.-S. Shih (2002). Jobs versus the environment: an industry-level perspective. *Journal of Environmental Economics and Management 43*(3), 412–436.

Sato, M., G. Singer, D. Dussaux, and S. Lovo (2014). International and sectoral variation in energy prices 1995-2011: how does it relate to emissions policy stringency? GRI Working Papers 187, Grantham Research Institute.

Walker, W. R. (2011). Environmental regulation and labor reallocation: Evidence from the Clean Air Act. *The American Economic Review 101*(3), 442–447.

Walker, W. R. (2013). The transitional costs of sectoral reallocation: evidence from the Clean Air Act and the workforce. *The Quarterly Journal of Economics 1787*, 1835.