Environment versus Jobs: An Industry-level Analysis of Sweden

Golnaz Amjadi

The Centre for Environmental and Resource Economics (CERE) is an inter-disciplinary and inter-university research centre at the Umeå Campus: Umeå University and the Swedish University of Agricultural Sciences. The main objectives with the Centre are to tie together research groups at the different departments and universities; provide seminars and workshops within the field of environmental & resource economics and management; and constitute a platform for a creative and strong research environment within the field.

Department of Economics, Umeå University, S-901 87,
Umeå, Sweden www.cere.se

Environment versus Jobs: An Industry-level Analysis of Sweden

Golnaz Amjadi^{1,2}

¹Umeå University, Centre for Environmental and Resource Economics (CERE)

²STATEC Research (National Institute of Statistics and Economic Studies)

Abstract

The aim of this paper was to investigate whether the environment and employment compete with each other in Swedish manufacturing industry. The effect of a marginal increase in environmental expenditure and environmental investment costs on sector-level demand for labor (employment) was studied using a detailed firm-level panel dataset for the period 2001–2008. The results showed that the sign and magnitude of the net employment effects ultimately depend on the aggregate sector-level output demand elasticity. If the output demand is inelastic, these costs induce small net improvements in employment, while a more elastic output demand suggests negative, but in most sectors relatively small, net effects on demand for labor. Hence, the results did not generally indicate a substantial trade-off between jobs and the environment. The general policy recommendation that can be drawn from this study is that, in the absence of empirically estimated output demand elasticities, a careful attitude regarding national environmental initiatives for sectors exposed to world market competition should be adopted.

JEL classification : C33, D22, J23, K32

Keywords: Environmental expenditure and environmental investment costs, output demand elasticity.

1 Introduction

In public debates about environmental regulations, concerns are raised about a potential “jobs versus the environment” conflict. Labor unions and trade groups argue that environmental regulations impose extra costs on producers which reduce production level and demand for labor. An alternative to this pessimistic perspective on environmental regulations is the concept of “green jobs” which became part of the policy discussion in recent years. This alternative argues that “green jobs” can solve challenges related both to climate change and to high rates of unemployment in industrialized countries.

Empirical studies have not always found a win-win outcome of ambitious green policies. The evidence is mixed at best, at least for most of the studies, which have been based on data from the U.S. (see e.g., Berman and Bui, 2001, Morgenstern et al., 2002, and Greenstone, 2002). For example, Berman and Bui (2001) and Morgenstern et al. (2002) found in general no substantial effects of environmental regulations on employment. In contrast, Kahn (1997), Shadbegian and Akofio-Sowah (2001), and Greenstone (2002) showed that such regulations have negative effects on employment. Greenstone (2002) noted that regulations may decrease employment within some sectors, but that the affected workers would normally still be utilized elsewhere in the economy. It is possible that losses due to environmental regulation are the adjustment or frictional costs associated with the shifting resources to new sectors, implying that a “green job” (created by policy) is likely to come at the expense of a “brown job” (which is lost). Even in the absence of any job creation (i.e. if there is no net increase in employment), one may observe a shift from “brown” to “green” jobs, and this change is presumably beneficial to society as a whole. Therefore, although pro-environmental actions may have a small or limited net employment effect, their effects on the structure of the economy might nevertheless be substantial.

At present, the various issues raised above have not yet been fully investigated in European countries (where worker protection laws are typically stronger) and we simply do not know enough about the effects of pro-environmental costs on labor demand. Therefore, the aim of this study is to begin investigation of these issues by estimating the effects of a marginal increase of environmental expenditure and environmental investment costs on sector-level employment. Environment-related costs and expenses incurred by producers are assumed to be induced by regulation. For this purpose, I analyze a firm-level panel dataset covering 11 sectors in the Swedish manufacturing industry over the years 2001–2008 within the general framework proposed by Morgenstern et al. (2002), and assume that firms minimize their cost with respect to two distinct activities: conventional production and environment-related activities. Environment-related costs initiate a sequence of changes that may ultimately change demand for labor within a sector. For instance, a firm may increase output

price and change its production level because of such costs, which, in turn, may change employment in that firm; such changes in a number of firms will result in change at the sector level.

To the best of my knowledge, the majority of previous empirical research in this area has been performed on data from U.S., and whether those conclusions apply to European countries is questionable. Specifically, no previous studies have empirically examined the relationship between environmental-related costs and labor demand at sector level for the Swedish manufacturing industry. Therefore, it is my hope that this study will provide further insights about the effects of environmental-related costs on sector-level labor demand, with the goal of contributing significantly to policy design.

This paper is organized as follows. Section 2 briefly reviews contemporary empirical studies about the relationship between environmental regulations and employment. Section 3 outlines the theoretical framework and empirical specification applied, and section 4 describes the firm-level dataset used. The results are presented in section 5, which are then discussed in section 6.

2 Literature Review

Survey-based measures of environmental abatement costs and expenditure suggest that environmental regulations impose additional operational and capital costs to manufacturers. For instance, a study by the United States Census Bureau (2008) revealed that the Clean Air Act (CAA)¹ in the United States has \$20.6 billion in annual operating costs and \$5.9 billion in capital expenditures. Manufacturers generally argue that these costs place them at a competitive disadvantage to such an extent that plants might decrease production or even close. In either case, these costs have negative impacts on employment.

Relatively few empirical studies have investigated how (or indeed even whether) regulatory-induced environmental costs affect demand for labor (or employment) in regulated sectors by comparing data from before and after a new regulation is imposed. By far most of the studies have been performed on data from the U.S. (see e.g. Berman and Bui, 2001; Morgenstern et al., 2002; Greenstone, 2002; and Belova et al., 2015), and these studies generally showed small effects, either positive or negative, on employment.

Morgenstern et al. (2002) investigated the trade-off between the environment and jobs by taking environmental costs as a proxy for environmental regulations and seeing how these regulations affected labor demand. Their analysis was performed on four polluting sectors of U.S. manufacturing: pulp and paper, plastic material, petroleum, and steel, using plant-level panel dataset. They found that increased spending on abatement activities did not cause any notable change in employment. Statistically significant and small positive effects were found in two of the sectors, namely petroleum and plastic material. Within these sectors, abatement activities were relatively more labor intensive than production activities. Hence, holding the output constant, employment increased due to environmental costs imposed by the regulations. Furthermore, the positive employment effect was not offset due to demand response, because output demand is relatively price inelastic within these sectors.

Some other studies (Kahn, 1997 and Greenstone, 2002) found that regulations had negative effects on industrial employment. Kahn (1997) used annual data about U.S. manufacturing employment at the county-level and showed that non-attainment counties (those with lower air quality than national standards) had lower employment growth rates. Attainment counties were less regulated because they complied with the CAA's standards. Less regulation may relatively lower production costs and encourage economic growth in such counties because producers prefer to be located there, which has the overall effect of diverting economic activities to attainment and non-monitored counties.

¹ The Clean Air Act (CAA) is one of most influential environmental laws in U.S. aiming to control air pollution at the national level. The U.S. Environmental Protection Agency administers CAA.

Greenstone (2002) used 1.75 million plant-level observations to compare the effects of the CAA on industrial activity between pollutant-specific non-attainment counties (with air quality below the CAA standard) and attainment counties. He found that non-attainment counties lost about 590,000 jobs during the first 15 years of CAA amendments (1972–1987) compared to the non-regulated counties. This loss was less than 4% of the total employment in manufacturing sector over the studied period. These results did not represent the total effects of environmental regulations on employment, but rather indicated the relative growth of pollution-intensive manufacturing activities in non-attainment counties compared to attainment counties.

Another pair of studies (Walker 2011, 2013) studied whether higher emission standards under the CAA amendments affected employment. Walker (2011) applied a plant-level U.S. dataset for the period 1985–2005 and showed that the more restrictive emission standards introduced in the early 1990s permanently ended certain jobs instead of merely reducing hiring rates in the regulated sectors, leading to a shift in production and employment away from newly regulated sectors. He showed that the size of the regulated polluting sector was reduced by 15% over ten years after the change in regulation. This job loss was linked to a major adjustment in labor demand through an almost doubled rate of firing in the newly regulated plants. In a later study, Walker (2013) estimated the transitional costs linked to reallocating labor from newly regulated industries to other sectors that were thought to be due to environmental regulation induced by the 1990 CAA amendments. He used a worker-firm level dataset and found that workers experienced more than \$5.4 billion forgone earnings mainly due to non-employment and lower earnings in future employment for the years after the policy change. However, in relation to the estimated benefits of the 1990 CAA amendments, these one-time transitional costs were small. He also estimated how firms and workers respond to gradual changes in regulation, concluding that at the aggregate level, employment decreased in the regulated sector. However, the wages for the remaining labor did not fall.

Kahn and Mansur (2013) used plant-level data from the U.S. from 1998–2009 and showed that employment within pollution-intensive industries was higher among counties with less strict CAA regulations. Berman and Bui (2001) used plant-level data to estimate the effects of increased air quality regulation in Los Angeles on the pollution control capital investments, employment, and value added during the period 1979–1992. Although the regulation reduced NO_x emissions and increased large abatement investments, they found that local air quality regulation had no substantial negative effect on employment, since regulated plants belong into capital-intensive industries rather than labor-intensive ones.

Gray et al. (2014) used plant-level data from the Census of Manufacturers and Annual Survey of Manufacturers at the U.S. Census Bureau from 1992–2007

to examine how the “Cluster Rule” affected labor demand within pulp and paper sector. “Cluster Rule” is the Environmental Protection Agency (EPA)’s first integrated regulation aimed at mitigating both air and water pollution from the pulp and paper industries. They found general small negative effects on employment, ranging between 3–7%, which was sometimes statistically significant. They also found that plants that were regulated only with regard to their air pollution experienced positive effects on employment, although these changes were generally statistically insignificant.

Ferris et al. (2014) used a panel dataset of fossil fuel fired power plants to study how phase I of EPA’s SO₂ trading program affected employment within electric power plants. The study found little evidence that plants facing the first phase of the SO₂ trading program had significant decreases in their employment levels relative to the non–Phase I power plants.

Gray and Shadbeigian (2013) analyzed the effect that environmental regulation had on employment in U.S. manufacturing using data from 1973–1994. Their estimates suggested that higher levels of environmental regulation reduced the level of employment. Although these estimates were statistically significant, they were very small in magnitude.

As previously mentioned, studies outside U.S. are rare. However, there have been few recent attempts to study how environmental regulation affects employment. To address this question, Golombek and Raknerud (1997) looked at data from polluting firms in three sectors (Pulp, paper, and paperboard; Iron, steel, and ferroalloys; Basic industrial chemicals) in Norway. They showed that environmental regulations tended to have a positive impact on firms’ employment levels in two of the sectors (Pulp, paper, and paperboard and Iron, steel, and ferroalloys). Cole and Elliot (2007) used a framework similar to Berman and Bui (2001) on UK industry-level data covering 27 industries for 1999–2003. They concluded that environmental regulation costs generally had a negative but statistically insignificant effect on employment, implying that environmental regulation did not cost jobs. Liu et al. (2017) used two Chinese enterprise-level datasets to estimate the effects of a stricter wastewater discharge standard on all the textile printing and dyeing enterprises. They showed that enterprises that faced the more stringent standard reduced their labor demand by about 7%.

Another group of studies instead estimated the effects of membership in the European Union Emissions Trading Scheme (EU-ETS)² on employment. Anger and Oberndorfer (2008) used data on 419 German firms during first phase of EU-ETS (2005–2007) to see how this scheme affected employment levels in Germany. They found no significant effects on the level of employment among the regulated German firms during the first phase. Abrell et al. (2011) used a firm-

² The EU emissions trading system (EU ETS) is a fundamental EU policy to combat climate change. This system aims to reduce greenhouse gas emissions and is the world’s first major carbon market.

level panel dataset on emission levels and performance of more than 2000 European firms from 2005–2008 to investigate the effect of EU-ETS on employment, finding that the EU-ETS did not affect firms' employment levels during the studied period. Chan et al. (2013) used a panel dataset covering about 6000 firms in 10 European countries from 2005–2009, and investigated the effects of EU-ETS on firms' employment levels across the three most polluting sectors (Power, Cement, and Iron and steel). They concluded that EU-ETS had no negative effects on employment levels during the studied period.

The main conclusions from this literature review are the following. First, empirical evidence suggested a range of regulatory effects, from positive to negative, but these effects were always relatively small in magnitude. Second, because the majority of studies used data from the U.S., a research gap exists regarding European countries. Given availability of detailed micro-level data, one can further investigate how environmental policy affects employment and labor demand outside US.

3 Theoretical and Empirical Framework

In this paper, I estimate the impact of a marginal increase in environmental expenditure and environmental investment costs by firms on the sector-level employment (or labor demand). For this purpose, I implement the general framework of Morgenstern et al. (2002) with some modifications.³

Each firm minimizes its costs with respect to two main distinct activities: conventional production activities to produce marketed goods Y , and environmental activities to produce an environmental output R . A firm's total cost (TC) is the sum of production costs (PC) and environment-related costs (EMC) associated with production of Y and R , i.e. $TC=PC+EMC$.

Environment-related costs include environmental expenditures and environmental investments and are hereafter referred to as environmental management cost (EMC). $EMCs$ are assumed to be regulatory-induced. How a marginal increase in EMC affects employment may differ depending on the extent to which a firm rearranges its production activities and changes its production level. As explained later in this section, the total net effect of a marginal increase in EMC on labor demand is ambiguous and remains an empirical question. Theoretically, $EMCs$ initiate a sequence of changes that may ultimately change demand for labor, a process that is detailed below.

3.1 The Effect of $EMCs$ on Firm-level Labor Demand

Following Morgenstern et al. (2002), Eq. (1) presents the labor demand or employment for firm i and year t as;

$$L_{it} = \frac{1}{p_{l,it}} v_{l,it} TC_{it} \quad (1)$$

where L denotes the number of full-time employees devoted to either production or environmental activities, p_l is the labor price (yearly salary), v_l is the labor cost share, and TC is the total costs related to both production and environmental activities. Differentiating Eq. (1) with respect to EMC , holding the output level Y constant, shows how EMC affects firm i 's employment:

$$\left. \frac{\partial L_{it}}{\partial EMC_{it}} \right|_{Y=Y} = \underbrace{\frac{v_{l,it}}{p_{l,it}} \frac{\partial TC_{it}}{\partial EMC_{it}}}_{\text{cost effect}} + \underbrace{\frac{TC_{it}}{p_{l,it}} \frac{\partial v_{l,it}}{\partial EMC_{it}}}_{\text{factor shift effect}} \quad (2)$$

³ A few modifications to Morgenstern et al. (2002)'s framework have been made to improve the model specification. These are discussed as they are introduced.

Eq. (2) has two components: cost effect and factor shift effect, both of which are explained under the assumption that firm holds the same level of production of output Y after $EMCs$ are taken. For abatement activities, a firm demands more of all inputs including labor, which increases the total production costs and is referred to as *cost effect*. Cost effect always has a positive effect on a firm's labor demand. Furthermore, using labor in environment-related activities may change labor intensity in the total production activities, which means that the production of Y and R as a whole may become more or less labor intensive than conventional production technology. This process is referred to as the *factor shift effect* and how and whether it affects labor demand is an empirical question. This effect may be different in different sectors. If environmental activities within one sector are more labor-intensive relative to conventional production activities, the factor shift effect increases the level of employment, and *vice versa*.

3.2 The Aggregate Effect of EMC on Sector-Level Demand for Labor

The effect of a marginal increase in EMC on sector-level employment can be obtained by aggregating the firm-level effects on employment. It is reasonable to assume that within each sector, the EMC for firm i in year t is proportional to its total cost relative to total cost of the sector to which this firm belongs, i.e. $\partial EMC_{it}/\partial EMC_{agg} = TC_{it}/TC_{agg}$ (Morgenstern et al., 2002). This proportionality implies that a larger firm has a relatively larger contribution to pro-environmental activities. Similar to Gray (2018), I assume that EMC provides no additional benefits to the producer other than those for satisfying the pro-environmental purposes, i.e., if everything else is kept the same, $\partial TC_{it}/\partial EMC_{it} = 1$. This means that one Swedish krona (SEK) of increased EMC would increase a firm's TC by one SEK.⁴ Under these assumptions, the impact of a marginal increase in EMC on aggregate sector-level employment for a sector with i firms ($i = 1, \dots, I$) over a period of t years ($t = 1, \dots, T$) is given by:

⁴ Morgenstern et al. (2002) did not make this assumption. However, their empirical findings do not contradict this assumption. They assumed that there might be uncounted savings in production costs associated with environmental expenditures, meaning that a 1 SEK increase in environmental expenditures would reflect less than 1 SEK increased total costs. However, they generally did not find evidence of such uncounted savings in production costs associated with environmental expenditures.

$$\begin{aligned}
\left. \frac{\partial L_{agg}}{\partial EMC_{agg}} \right|_{Y=\bar{Y}} &= \sum_{i=1}^I \sum_{t=1}^T \frac{\partial L_{it}}{\partial EMC_{agg}} \\
&= \sum_{i=1}^I \sum_{t=1}^T \overbrace{\frac{\partial L_{it}}{\partial EMC_{it}}}^{=Eq.(2)} \overbrace{\frac{\partial EMC_{it}}{\partial EMC_{agg}}}^{=\frac{TC_{it}}{TC_{agg}}} \\
&= \sum_{i=1}^I \sum_{t=1}^T \left(\underbrace{\frac{v_{l,it}}{p_{l,it}} \frac{\partial TC_{it}}{\partial EMC_{it}}}_{=1 \text{ cost effect}} + \underbrace{\frac{TC_{it}}{p_{l,it}} \frac{\partial v_{l,it}}{\partial EMC_{it}}}_{\text{factor shift effect}} \right) \frac{TC_{it}}{TC_{agg}} \\
&= \frac{1}{TC_{agg}} \sum_{i=1}^I \sum_{t=1}^T \frac{TC_{it}^2}{p_{l,it}} \frac{\partial v_{l,it}}{\partial EMC_{it}} + \frac{L_{agg}}{TC_{agg}}
\end{aligned} \tag{3}$$

So far, it has been shown how a marginal change in *EMC* affects employment in the individual firm as well as in an entire sector, holding output constant. The following sub-section discusses the effects of increased *EMCs* on output demand and production level.

3.3 The Aggregate Demand Effect on Sector-Level Employment

EMCs increase total production costs, which then increase output price and reduce the demand for output. Hence, a firm's demand for all inputs, including labor, decreases. This relationship is called the *demand effect* for labor, and the magnitude of this effect differs depending on the extent to which increased costs are passed on to the consumers and the price elasticity of the aggregate output demand. These last-named features may be related. For instance, sectors facing a competitive market and an elastic output demand may lower their costs of environmental compliance, while less competitive sectors with an inelastic demand for output may be less concerned about increased *EMC* (Morgenstern et al., 2002). The mechanism behind a negative relationship between costs and output demand can be explained by a two-step procedure through changes in output prices. These two steps in turn depend on several factors such as the degree of market competition and the effects of environmental and other policies.

Similar to Morgenstern et al., (2002), a market structure with monopolistic competition is assumed to reflect, for example, non-price differences among products within each sector. The sector-level aggregate demand effect is formulated assuming, first, that the aggregate demand for the sector-level output exhibits a constant demand elasticity ε_d ; second, for each firm, the output price increases proportionally with the firm's total cost; third, the demand for a firm's output falls proportionally with the aggregate demand for

that sector's output. Furthermore, it is assumed that firm-level employment decreases proportionally with the output demand. Adding up these firm-level effects, the change in aggregate labor demand can be written as:

$$\left. \frac{\partial L_{agg}}{\partial EMC_{agg}} \right|_{Demand\ effect} = -\varepsilon_d \overbrace{\frac{\partial TC}{\partial EMC}}^{=1} L_{agg} \quad (4)$$

where ε_d represents the sector-level aggregate output demand elasticity, and L_{agg} is the aggregate demand for labor. Eq. (4) shows the effect of a marginal increase in EMC on the aggregate demand for labor due to the demand effect.

In this study, no attempt is made to estimate ε_d , which is a variable that deserves a study in its own right. Given a high degree of uncertainty regarding its magnitude, instead, a sensitivity analysis is performed to relate the demand effect to the empirically estimated cost and factor shift.

3.4 Total Net Effect of $EMCs$ on Sector-Level Labor Demand

The total net effect of a marginal increase in EMC on the aggregate labor demand within a sector is obtained by adding up the factor shift effect, cost effect and demand effect represented by Eq. (3) and Eq. (4). Doing so results in:

$$\frac{\partial L_{agg}}{\partial EMC_{agg}} = \overbrace{\frac{1}{TC_{agg}} \sum_{i=1}^I \sum_{t=1}^T \frac{TC_{it}^2}{p_{l,it}} \frac{\partial v_{l,it}}{\partial EMC_{it}}}^{\text{Aggregate Factor Shift Effect}} + \overbrace{(1 - \varepsilon_d) \frac{L_{agg}}{TC_{agg}}}^{\text{Aggregate Cost and Demand Effect}} \quad (5)$$

Eq. (5) allows for dividing the total net employment effect into separate components. This equation isolates the demand effect from the total net effect. If the total net effect is positive, but the demand effect is large and negative, it suggests that labor unions and trade groups might have valid concerns about the negative effects of $EMCs$ on the competitiveness. However, their focus on employment would be wrong (Morgenstern et al., 2002).

Given the availability of data on number of employees, salaries, and other costs, all terms in the right hand side of Eq. (5) can be directly obtained from the dataset except for $\partial v_{l,it} / \partial EMC_{it}$ and ε_d . These two terms need to be estimated. To recap, $v_{l,it}$ is the labor cost share for firm i in year t , associated with labor engaged in the production of either marketed goods Y or environmental output R . Section 3.5 presents the framework used in this paper to derive the labor-cost share $v_{l,it}$ and estimation issues. ε_d is the aggregate output price elasticity of demand which has not yet been estimated for Sweden in any study at sector or industry-level to the author's knowledge. Estimating these elasticities remains as an important

research question for future studies and is outside the scope of this paper. In the absence of empirical estimates, the approach used in this study is to provide a sensitivity analysis of the results over a broad range of values for output demand elasticity, ranging from no demand response ($\varepsilon_d = 0$) to a highly elastic negative demand response ($\varepsilon_d = -16$).⁵ This broad range of values still provides intuition regarding the effect of elasticity on the sign and magnitude of the total net effect of a marginal increase in *EMC* on the labor demand in the different sectors.

3.5 Derivation of Labor Cost Shares and Cost Effect

As previously mentioned, $v_{l,it}$ is the labor cost share linked to labor engaged in the production of either conventional output *Y* or environmental output *R*. For a cost-minimizing firm *i* in year *t*, the cost functions *PC* and *EMC* are formulated as⁶ :

$$\ln PC_{it} = \alpha_i D_i + \alpha_t D_t + \alpha_x \ln P_{x,it} + \alpha_{x,i} D_i \ln P_{x,it} + \alpha_{x,t} D_t \ln P_{x,it} + \alpha_y \ln Y_{it} + \frac{1}{2} \beta_{yy} (\ln Y_{it})^2 + \frac{1}{2} \ln P'_{x,it} \beta_{xx} \ln P_{x,it} + \beta_{yx} \ln Y_{it} \ln P_{x,it} \quad (6)$$

$$\ln EMC_{it} = \gamma_x \ln P_{x,it} + \gamma_r \ln R_{it} + \frac{1}{2} \ln P'_{x,it} \delta_{xx} \ln P_{x,it} + \delta_{ttx} \ln P_{x,it} + \gamma_{tt} \ln R_{it} \quad (7)$$

where

$$\sum \alpha_x = \sum \gamma_x = 1, \sum \beta_{yx} = \sum \beta_{xx} = \sum \delta_{xx} = 0 \text{ for } x \in \{l, k, e\}$$

lnPC and *lnEMC* are translog cost functions for producing a given level of *Y* and *R*, respectively. *lnPC* is a non-homothetic cost function and homogenous of degree one in input prices, while *lnEMC* is a homothetic function (i.e. has no scale bias⁷) and homogeneous of a constant degree. *P* is a vector of input prices for labor, capital and energy, where subscript $x \in \{l, k, e\}$. *D_i* and *D_t* are vectors of firm and year dummies, respectively, and *tt* is a time trend variable. The firm fixed effects control for unobserved firm-level heterogeneity, while the time fixed effects control for year heterogeneity. Because of the lack of data on environmental output *R*, the *EMC* function in Eq. (7) is assumed to be homothetic, which implies that the input cost shares associated with environmental activities are independent of *R*.

⁵ This value was selected as an example of a high price elasticity for the sensitivity analysis.

⁶ Production cost function in Morgenstern et al. (2002) includes an interaction term between environmental and production costs. However, they did not consider this term when they derived input cost shares. Furthermore, the coefficient estimate of this term did not become statistically significant in the majority of studied sectors.

⁷ The empirical estimation was also performed where *lnPC* is a homothetic function. The results are generally similar.

The standard approach for deriving a system of cost-minimizing input cost shares is to differentiate the logarithm of the cost function with respect to the logarithm of input prices. Each input cost share $v_{x,it}$ reflects the costs associated with the use of that input in conventional production activities, denoted as $v_{x,it,Y}$ as well as environmental activities, denoted as $v_{x,it,R}$. Data on $v_{x,it,Y}$ and $v_{x,it,R}$ are not available separately, but the total cost shares $v_{x,it}$ can be observed from the dataset. Following Morgenstern et al. (2001, 2002), one can distinguish between $v_{x,it,Y}$ and $v_{x,it,R}$ in the following way. Given the specification of $\ln PC$ in Eq. (6), the input cost shares associated with production of output Y are written as functions of input prices $\mathbf{P}$ and output level Y :

$$v_{x,it,Y} = \frac{\partial \ln PC_{it}}{\partial \ln P_{x,it}} = \alpha_x + \alpha_{x,t} \mathbf{D}_t + \alpha_{x,t} \mathbf{D}_t + \beta'_{xx} \ln \mathbf{P}_{x,it} + \beta_{yx} \ln Y_{it} \quad (8)$$

while the input cost shares linked to environmental activities are derived from Eq. (7) and are functions of the input prices:

$$v_{x,it,R} = \frac{\partial \ln EMC_{it}}{\partial \ln P_{x,it}} = \gamma_x + \delta'_{xx} \ln \mathbf{P}_{x,it} + \delta_{tx} tt \quad (9)$$

Assuming three production factors *labor* (l), *capital* (k) and *energy* (e), Morgenstern et al. (2001, 2002) specified the observed cost share for input $x \in \{l, k, e\}$ as:

$$\begin{aligned} v_{x,it} &= \left(\frac{EMC_{it}}{EMC_{it} + PC_{it}} \right) v_{x,it,R} + \left(1 - \frac{EMC_{it}}{EMC_{it} + PC_{it}} \right) v_{x,it,Y} \\ &= v_{x,it,R} + \left(\frac{PC_{it}}{EMC_{it} + PC_{it}} \right) (v_{x,it,Y} - v_{x,it,R}) \end{aligned} \quad (10)$$

Eq. (10) expressed the total cost share for each input as a weighted average of the cost shares associated with environmental and conventional production activities, producing the outputs R and Y , respectively. The weights are the ratio of EMC and PC , respectively, to the TC (where $TC_{it} = EMC_{it} + PC_{it}$).

For each firm and year, the sum of input cost shares over all equations adds up to unity, i.e. $\sum_{x \in \{l,k,e\}} v_{x,it} = 1$. Hence, with three input cost share equations for capital, labor, and energy only two of them are linearly independent. For estimation, homogeneity restrictions are imposed by normalizing labor and energy prices as well as PC and EMC with respect to the capital price. Capital cost share is excluded from the system. The remaining input cost shares represented by Eq. (10) are estimated as a system of equations using the iterative 3-stage least square (3SLS) estimator while assuming cross-equation

symmetry conditions and homogeneity of degree one in prices.⁸ This estimator was chosen because it guarantees that parameter estimates are invariant to the choice of input cost share excluded from the system (Berndt, 1990).

Recall that, in order to evaluate the total net effect of EMC on the aggregated employment, $\partial v_{l,it}/\partial EMC_{it}$ must be obtained, see Eq. (5). Because the cost shares $v_{l,it,Y}$ and $v_{l,it,R}$ do not depend on EMC , it follows from Eq. (10) that:

$$\frac{\partial v_{l,it}}{\partial EMC_{it}} = -\frac{PC_{it}}{(EMC_{it} + PC_{it})^2} (v_{l,it,Y} - v_{l,it,R}) \quad (11)$$

Substituting Eq. (8) and Eq. (9) for the input labor into Eq. (11) gives:

$$\begin{aligned} \frac{\partial v_{l,it}}{\partial EMC_{it}} = & -\frac{PC_{it}}{(EMC_{it} + PC_{it})^2} (\alpha_l + \alpha_{l,i} \mathbf{D}_i + \alpha_{l,t} \mathbf{D}_t + \beta_{ll} \ln NP_{l,it} + \beta_{le} \ln NP_{e,it} \\ & + \beta_{yl} \ln Y_{it} - \gamma_l - \delta_{ll} \ln NP_{lit} - \delta_{le} \ln NP_{eit} - \delta_{tllt}) \end{aligned} \quad (12)$$

where NP_l and NP_e denote relative prices for the inputs labor and energy to the capital price, which is normalized to one. Finally, Eq. (12) is substituted into Eq. (5) in order to evaluate the total net effect of a marginal increase in $EMCs$ on the sector-level employment. The total net effect can be written as:

$$\begin{aligned} \frac{\partial L_{agg}}{\partial EMC_{agg}} = & \frac{1}{TC_{agg}} \sum_{i=1}^I \frac{TC_{it}^2}{p_{l,it}} \left(-\frac{PC_{it}}{(EMC_{it} + PC_{it})^2} (\alpha_l + \alpha_{l,i} \mathbf{D}_i + \alpha_{l,t} \mathbf{D}_t + \beta_{ll} \ln NP_{l,it} \right. \\ & + \beta_{le} \ln NP_{e,it} + \beta_{yl} \ln Y_{it} - \gamma_l - \delta_{ll} \ln NP_{lit} - \delta_{le} \ln NP_{eit} \\ & \left. - \delta_{tllt}) \right) + (1 - \varepsilon_d) \frac{L_{agg}}{TC_{agg}} \end{aligned} \quad (13)$$

Eq. (13) represents the specification used and estimated separately for 11 sectors in the Swedish manufacturing industry. The first term in Eq. (13) represents the aggregate factor shift effect, while the second term expresses the joint aggregate cost and demand effects. A standard normal interval bootstrap estimation procedure proposed by Efron (1979) is used to estimate the standard errors of $\partial L_{agg}/\partial EMC_{agg}$ and each of its three components: cost effect, factor shift effect, and demand effect.

⁸ Eq. A.1 – A.4 in the Appendix show normalized translog PC function (NPC), normalized EMC function ($NEMC$) as well as labor and energy cost share functions following Eq. (10).

4 Data

I use a firm-level unbalanced panel dataset to study the relationship between the actual firm-level *EMC* and employment in the Swedish manufacturing industry. Statistics Sweden is the source of this dataset, which covers the period 2001–2008 and contains detailed information on costs and quantities related to different inputs, sales, etc., as well as information on environmental investments and expenditures. The sectors within the Swedish manufacturing industry covered in this study are: *Basic iron and steel, Chemical, Electro, Food, Machinery, Motor vehicles, Pulp and paper, Rubber and plastic, Stone and mineral, Textiles and Wood*. Table 1 presents descriptive statistics for the variables with all monetary values expressed in SEK and 2008 prices.

For each firm and year, output is an index calculated as a firm's final sales divided by its corresponding producer price index. The inputs are energy, labor, and capital. Energy is the sum of all renewable and non-renewable energy sources. Renewable energy consists of electricity, district heating and wood fuel, while non-renewable energy consists of coal, solid fuel and gaseous fuel. Statistics Sweden converts both renewable and non-renewable sources to energy equivalents (GWh) using the same conversion rates for all sectors. Labor is defined as the number of full-time employees.

The energy price for each firm and year is calculated by the ratio of total energy costs to the quantity of energy used. Yearly salary (labor price) for each firm and year is calculated by the ratio of total salaries to the number of employees, which reflects the average amount paid to a full-time employee by an average firm in each year.

The data also contain survey-based information on firm-level costs associated with environmental investments and environmental expenditure. As noted earlier, the sum of these costs is the environmental management cost *EMC*.

Table 1. Descriptive Statistics – Yearly Averages over 2001–2008

Sector	Output (MSEK)	Energy (GWh)	Labor (number)	Energy Price (SEK/MWh)	Salary (TSEK)	EMC (MSEK)
Basic iron and steel	36 418	18 331	15 622	481	669	455
Chemical	58 706	6 807	23 178	460	708	830
Electro	145 868	609	32 082	386	407	97
Food	68 235	3 686	30 018	474	506	568
Machinery	58 963	1 248	33 554	485	516	226
Motor vehicles	169 463	2 373	51 451	452	436	318
Pulp and paper	83 124	36 973	29 579	316	506	1 762
Rubber and plastic	6 273	510	4 829	486	497	50
Stone and mineral	11 215	3 685	9 257	445	494	225
Textile	2 504	259	2 485	432	388	19
Wood	20 614	2 441	7 590	254	459	75

The environmental data originates from the ‘Environmental protection expenditure in industry’ survey, administered by Statistics Sweden since 1999 with compulsory participation starting in 2001. The survey collects information on firm-level environmental investments and expenditures for a sample consisting of firms with at least 20 employees. Information from the survey covers three main categories: pollution treatment investment, pollution prevention investment, and current expenditure. Pollution treatment investments do not affect the production process and aim to deal with pollutants that are already made; these types of solutions are often referred to as ‘end-of-pipe’ solutions (Jaraite et al., 2014). Filters and scrubbers are examples of such investments. In contrast, pollution prevention investments attempt to directly affect the production process in order to reduce pollution. These are characterized by “(1) lowering emissions from production processes; (2) facilitating the use of less environmentally damaging input factors; (3) new and more efficient and less emitting equipment and machinery” (Jaraite et al.; 2014, pp: 164). Optimizing the use of chemicals and increasing recycling are examples of such investments. The survey data on both pollution treatment and prevention costs are each disaggregated to components air, water and waste. Finally, current expenditure relates to some costs that are not considered to be investments, but that concern pre-existing equipment or operational activities. For instance, current expenditure can include costs of personnel, material and energy used for existing environmental facilities and management. These costs are divided into internal costs and hired services. Financial costs like depreciation and environmental taxes and fees are not included (Jaraite et al., 2014).⁹ Table 2 presents *EMC* as share of firms’ total costs for the period 2001–2008.

⁹ For more detailed information on the definitions of environmental investment and expenditure variables and examples, see Jaraite et al. (2014).

Table 2. Share of *EMC* in *TC* (%) for 2001–2008

Sector	EMC/TC (%)								
	2001	2002	2003	2004	2005	2006	2007	2008	Total
Basic iron and steel	2.24	2.10	1.70	2.39	3.04	3.77	3.95	3.16	2.70
Chemical	3.52	3.09	2.37	2.56	3.12	2.76	6.54	4.12	3.21
Electro	0.80	0.25	0.28	0.58	0.72	0.44	0.46	0.86	0.52
Food	2.52	2.17	2.11	2.31	2.73	2.53	6.53	2.61	2.90
Machinery	1.20	1.02	1.28	1.17	1.06	0.97	0.82	1.50	1.13
Motor vehicles	1.32	1.16	0.82	1.20	1.02	0.96	0.97	0.88	1.03
Pulp and paper	7.34	5.47	6.68	5.87	5.51	4.97	4.26	4.79	5.55
Rubber and plastic	2.05	1.69	1.41	2.24	2.14	1.42	1.62	1.65	1.74
Stone and mineral	2.51	3.16	3.12	4.17	4.07	4.78	6.71	3.81	3.99
Textile	1.60	1.63	2.01	1.81	1.78	1.35	1.28	1.68	1.65
Wood	1.60	1.54	1.49	1.27	1.66	1.95	2.07	1.71	1.64
Total	2.83	2.30	2.39	2.52	2.63	2.50	2.89	2.60	2.57

In general, the share of *EMC* in relation to total production costs is low (on average 2.57%). It varies notably between sectors, from 0.52% in the *Electro* sector to 5.55% in the *Pulp and paper* sector. The time variation is relatively low, averaging between 2.30% and 2.89% over the studied years and sectors.

5 Results

Table 3 presents point estimates for the total net employment effects of a marginal increase in EMC ($\partial L/\partial EMC$) presented in Eq. (13) and bootstrap estimates of their standard errors. Among the studied sectors and scenarios, the estimated net employment effects are, with few exceptions, statistically significant and range between net job losses and relatively modest net job gains per MSEK of increased $EMCs$. However, the effects vary substantially among industrial sectors and depend heavily upon the assumptions regarding the aggregate price elasticity of output demand. Because the effects are measured over a multi-year period, the net employment effects $\partial L/\partial EMC$ can be accurately interpreted “for an average year” during the period of interest. For instance, a net employment effect of -0.5 jobs per MSEK for the period would imply that an increase in $EMCs$ by 4 MSEK corresponds to a net loss of two average yearly salaries. The effects are measured separately within each sector only, and do not account for labor mobility among sectors and other dynamic effects within the economy as a whole, and hence assume that employment levels in other sectors remain constant.

If the aggregate demand is completely price inelastic, i.e. $\varepsilon_d = 0$, the results generally suggest relatively small but statistically significant (at the 95% confidence level) positive net effects on employment, ranging from 0.08 to 0.18 jobs per MSEK spent on EMC among the studied sectors (insignificant estimates range from 0.05 to 0.18 jobs per MSEK). Furthermore, given a larger aggregate demand elasticity of, say, $\varepsilon_d = -2$, statistically significant net employment effects remain small but negative, ranging from -0.09 to -0.45 jobs per MSEK among the studied sectors (insignificant estimates range from -0.11 to -0.32 jobs per MSEK). If the aggregate demand is sufficiently elastic, $\varepsilon_d = -4$, statistically significant negative net employment effects are found within all the sectors. The employment effects for such scenarios range from -0.28 to -1.01 jobs per MSEK among the studied sectors. Finally, if aggregate demand is extremely price elastic, e.g. $\varepsilon_d = -16$, statistically significant negative net employment effects range from -1.42 to -4.33 jobs per MSEK among the studied sectors.

Obviously, the sign and magnitude of the net employment effects depend heavily on the assumed aggregate price elasticity of output demand. Therefore, it is interesting to evaluate the results based on an empirical break-even value for which the net employment effect is equal to zero. Table 3 includes estimates for such break-even elasticity values, ranging from -0.29 within the *Textile* sector to -1.25 within the *Stone and mineral* sector. The largest sectors in terms of $EMCs$ shares, as indicated by the weights in Table 3, are *Pulp and paper* (37%), with a break-even elasticity value of -0.76 and *Chemical* (18%), with a break-even elasticity value of -1.10. The results indicate that positive net employment effects

are found in sectors where the aggregate demand for the produced output is less price responsive than indicated by the break-even elasticity value, and *vice versa*.

Recall from the description of the theoretical and empirical framework (section 3) that the net employment effects are composed of three parts, namely the cost effect, the factor shift effect and the demand effect. The cost effects are theoretically expected to be positive. Empirically, this effect is positive and varies in different sectors from 0.10 to 0.28 jobs per MSEK of *EMC*. The estimated factor shift effect varies in sign among the sectors, but are all statistically insignificant except for *Pulp and paper*, *Electro* and *Motor vehicles*. In these three sectors, the factor shift effect is relatively small and negative, but statistically significant. These results suggest that environmental activities in most sectors are as labor intensive as conventional production activities.

Table 3. Estimated Effects of *EMCs* on employment level

		Basic iron and steel	Chemical	Electro	Food	Machinery	Motor vehicles	Pulp and paper	Rubber and plastic	Stone and mineral	Textile	Wood
		Estimated marginal effects on employment per MSEK of additional <i>EMCs</i>										
Cost Effect		0.11 (0.02)	0.10 (0.02)	0.28 (0.02)	0.19 (0.01)	0.18 (0.01)	0.17 (0.01)	0.11 (0.00)	0.17 (0.02)	0.15 (0.02)	0.19 (0.01)	0.22 (0.01)
Factor Shift effect		-0.01 (0.02)	0.01 (0.03)	-0.17 (0.03)	-0.01 (0.01)	-0.02 (0.02)	-0.03 (0.01)	-0.03 (0.01)	0.00 (0.17)	0.04 (0.17)	-0.13 (0.17)	-0.10 (0.17)
Demand effect	$\varepsilon_d = 0$	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	$\varepsilon_d = -2$	-0.21 (0.04)	-0.19 (0.04)	-0.55 (0.04)	-0.38 (0.02)	-0.35 (0.01)	-0.34 (0.01)	-0.22 (0.01)	-0.34 (0.04)	-0.29 (0.03)	-0.37 (0.03)	-0.44 (0.02)
	$\varepsilon_d = -4$	-0.43 (0.08)	-0.38 (0.08)	-1.11 (0.08)	-0.76 (0.04)	-0.71 (0.03)	-0.67 (0.02)	-0.44 (0.01)	-0.67 (0.07)	-0.59 (0.07)	-0.74 (0.05)	-0.88 (0.05)
	$\varepsilon_d = -16$	-1.72(0.32)	-1.52(0.31)	-4.44(0.31)	-3.05(0.14)	-2.83(0.10)	-2.69(0.09)	-1.76(0.05)	-2.69(0.29)	-2.34(0.26)	-2.97(0.21)	-3.53(0.18)
Total net Effect	$\varepsilon_d = 0$	0.10 (0.03)	0.10 (0.03)	0.10 (0.03)	0.18 (0.02)	0.16 (0.02)	0.14 (0.01)	0.08 (0.01)	0.17 (0.17)	0.18 (0.17)	0.05 (0.17)	0.12 (0.17)
	$\varepsilon_d = -2$	-0.12 (0.03)	-0.09 (0.04)	-0.45 (0.04)	-0.20 (0.02)	-0.19 (0.02)	-0.20 (0.02)	-0.14 (0.01)	-0.17 (0.17)	-0.11 (0.17)	-0.32 (0.17)	-0.32 (0.16)
	$\varepsilon_d = -4$	-0.33 (0.07)	-0.28 (0.08)	-1.01 (0.08)	-0.58 (0.03)	-0.55 (0.03)	-0.53 (0.02)	-0.36 (0.01)	-0.50 (0.17)	-0.40 (0.18)	-0.69 (0.17)	-0.76 (0.16)
	$\varepsilon_d = -16$	-1.62(0.31)	-1.42(0.30)	-4.33(0.30)	-2.87(0.14)	-2.67(0.10)	-2.55(0.09)	-1.68(0.04)	-2.52(0.31)	-2.16(0.29)	-2.92(0.24)	-3.41(0.22)
Break-Even Point		-0.89 (0.14)	-1.10 (0.21)	-0.37 (0.14)	-0.97 (0.11)	-0.90 (0.12)	-0.81 (0.12)	-0.76 (0.11)	-1.00 (0.72)	-1.25 (0.75)	-0.29 (0.73)	-0.56 (0.72)
Obs.		136	220	118	261	299	162	331	101	127	68	89
Weight		0.10	0.18	0.02	0.12	0.05	0.07	0.37	0.01	0.05	0.00	0.02
		Marginal effects on employment based on a 1% increase in <i>EMCs</i>										
Employment change (number of jobs)	$\varepsilon_d = 0$	0.32 (0.09)	0.67 (0.18)	0.10 (0.03)	0.85 (0.07)	0.36 (0.04)	0.38 (0.04)	1.48 (0.22)	0.08 (0.08)	0.35 (0.34)	0.01 (0.03)	0.09 (0.13)
	$\varepsilon_d = -2$	-0.40 (0.11)	-0.58 (0.27)	-0.44 (0.04)	-0.92 (0.07)	-0.43 (0.04)	-0.56 (0.04)	-3.17 (0.21)	-0.08 (0.08)	-0.21 (0.33)	-0.06 (0.03)	-0.24 (0.12)
	$\varepsilon_d = -4$	-1.11 (0.22)	-1.77 (0.49)	-0.97 (0.07)	-2.65 (0.14)	-1.24 (0.06)	-1.49 (0.07)	-6.28 (0.25)	-0.25 (0.09)	-0.78 (0.34)	-0.13 (0.03)	-0.57 (0.12)
	$\varepsilon_d = -16$	-5.40(1.02)	-9.09(1.94)	-4.19(0.29)	-13.14(0.62)	-6.03(0.23)	-7.09(0.25)	-29.60(0.77)	-1.25(0.15)	-4.17(0.57)	-0.55(0.04)	-2.55(0.16)
<i>EMC</i> elasticity of labor demand (%)	$\varepsilon_d = 0$	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	$\varepsilon_d = -2$	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
	$\varepsilon_d = -4$	-0.01 (0.00)	-0.01 (0.00)	0.00 (0.00)	-0.01 (0.00)	0.00 (0.00)	0.00 (0.00)	-0.02 (0.00)	-0.01 (0.00)	-0.01 (0.00)	-0.01 (0.00)	-0.01 (0.00)
	$\varepsilon_d = -16$	-0.03 (0.00)	-0.04 (0.00)	-0.01 (0.00)	-0.04 (0.00)	-0.02 (0.00)	-0.01 (0.00)	-0.10(0.00)	-0.03 (0.00)	-0.05 (0.00)	-0.02 (0.00)	-0.03 (0.00)

* Standard errors are presented within parentheses. ** Weight represents the proportion of sectoral to the total *EMCs* of studied sectors over 2001–2008.

The results presented so far show the impact of a marginal increase in *EMC* on the sector-level employment. In order to connect these results back to empirical data, I used the estimated total net impacts as well as the total *EMC* within each sector over the studied period to calculate the net employment effects resulting from a 1% increase in *EMC* within each sector, assuming that a 1% change is equivalent to a marginal change. The employment effects are then presented in both absolute and relative terms, where the latter can be interpreted as elasticities of labor demand with respect to changes in *EMCs* (referred to as *EMC* elasticity of labor demand, ε_{EMC}). Given that the aggregate demand elasticities range from $-16 \leq \varepsilon_d \leq 0$, the average net employments effects for the studied sectors ranged from a net job loss to a net job gain. In the case of an inelastic demand response scenario, i.e. $\varepsilon_d = 0$, the results suggested a net job gain within the Swedish manufacturing industry as a whole. In absolute terms, *Pulp and paper*, *Food*, *Chemical*, *Motor vehicles*, *Machinery*, *Stone and mineral*, and *Basic iron and steel* had the largest net job gains. The net job gains among the other sectors were closer to zero. In relative terms, the largest positive impact was on *Pulp and paper*. In the case of a higher elastic demand response, here represented by the scenario $\varepsilon_d = -4$, the largest net job losses due to 1% increase of *EMC* were found within *Pulp and paper* followed by the sectors *Food* and *Chemical*, while in relative terms *Pulp and paper* experienced the largest negative impact. In the case of an extremely high elastic demand response, here represented by the scenario $\varepsilon_d = -16$, the largest net job loss appeared in *Pulp and paper*, *Food* and *Chemical*. In relative terms, the negative impact of 1% additional *EMC* on employment was largest in *Pulp and paper*. Parameter estimates for the system of input cost shares given in Eq. (10) are presented in Table A.1 in the Appendix.

6 Discussion and Conclusion

In the “jobs versus the environment” debate, it is often claimed that environmental regulation increases total production costs and output prices, which in turn reduces the demand for output and thereby demand for labor (employment). Concerns regarding negative employment effects are particularly justified for firms with labor-intensive production that are operating in sectors exposed to world market competition (Deschenes, 2014). However, an analysis of the total net effects of increased *EMC* on sector-level employment entails assessing not only the demand effects, but also effects on both the production costs and the labor intensity in the production. The results of this study generally suggest that even for sectors with extremely high output price elasticity, the impact of marginal increases in *EMCs* on labor demand are relatively low.

EMCs in these sectors around the current level can be justified on a few different bases. First, these costs are generally low relative to total production costs. The average share of *EMC* is about 3% (ranging between 1–6% in studied sectors), implying that a 1% increase in *EMC* increases total costs by 0.03%. Second, markets may not be perfectly competitive and there may be market power to adjust output prices. Firms also may benefit from signaling their compliance with environmental regulations. Lastly, these sectors may be “compensated” by subsidies or tax exemptions, which to some extent may bear the *EMC*.

The results from this study indicate small but statistically significant positive cost effects on the level of employment in all studied manufacturing sectors. It is true that these positive cost effects may be partially, or wholly, offset by negative demand effects depending on the aggregate output price elasticity. However, the results generally suggest that substantial job losses due to environmental initiatives are unlikely unless the aggregate output price elasticity of demand is considerably high. If anywhere, such elasticities would be found in sectors exposed to world market competition.

From a national policy perspective for a small, open economy like Sweden, the implications for environmentally regulated firms exposed to world market competition are particularly crucial. For firms primarily operating on national or local markets, the output demand is likely to be less elastic and overall employment effects generally less severe, because reductions in output demand in some sectors likely would be balanced by increased demand for outputs produced in other sectors. However, exploring this scenario is outside the theoretical framework of this study. For firms exposed to world market competition, however, the output demand is likely to be relatively more price elastic and overall employment effects potentially more harmful, due to the risk that reduced sales and job opportunities will relocate to outside the Swedish economy. In such cases, the negative effects could be mitigated by harmonizing

the environmental policy within the relevant trading zone, e.g. the European Union, so that foreign competing firms are affected proportionally.

Overall, the results from this study do not indicate any substantial trade-off between jobs and the environment within the Swedish manufacturing industry, given that the demand effects are relatively small. This result is in line with findings of earlier studies such as Berman and Bui (2001), Morgenstern et al. (2002), Anger and Oberndorfer (2008) and Abrell et al. (2011) who found no substantial effects of environmental regulations on the level of employment. However, the results are sensitive to the aggregate output price elasticity of demand, and the general policy recommendation that can be drawn from this study is that, in the absence of empirically estimated demand elasticities, a careful attitude regarding national environmental policies for sectors exposed to world market competition should be adopted. The empirical estimate of sector-level aggregate output demand elasticities within the manufacturing industry remains an important area for future studies of the “jobs versus the environment” question. In particular, a comparison of such empirical estimates against the break-even elasticity values found in this study could potentially determine whether the effects of *EMC* on employment are positive or negative within specific sectors of the Swedish manufacturing industry.

References

Abrell, J., Ndoye Faye, A. and Zachmann, G. (2011) Assessing the impact of the EUETS using firm level data [Online], Available from: https://www.bruegel.org/wp-content/uploads/imported/publications/WP_2011_08_ETS_01.pdf [Accessed 8 January 2018].

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

Belova, A., Gray, W. B., Linn, J., Morgenstern, R. D. and Pizer, W. (2015) Estimating the job impacts of environmental regulation, *Journal of Benefit Cost Analysis*, vol.6 pp. 325 – 340.

Berman, E. and Bui, L. T. M. (2001) Environmental regulation and labor demand: evidence from the South Coast Air Basin, *Journal of Public Economics*, vol.79 pp. 265 – 95.

Berndt, E. R. (1990) *The Practice of Econometrics: Classic and Contemporary*, New York, NY: Addison-Wesley.

Chan, H. S. R., Li, S. and Zhang, F. (2013) Firm competitiveness and the European Union Emissions Trading Scheme, *Energy Policy*, vol.63 pp. 1056 – 1064.

Cole, M. A., and Elliot, R. J. (2007) Do environmental regulations cost jobs? An industry-level analysis of the UK, The B. E. *Journal of Economic Activity & Policy*, vol.7 pp. 1 – 25.

Deschenes, O. (2014) Environmental regulations and labor markets [Online], Available from: <https://wol.iza.org/articles/environmental-regulations-and-labor-markets/long> [Accessed 8 May 2018].

Efron, B. (1979) Bootstrap methods: another look at the jackknife, *The Annals of Statistics*, vol.7(1) pp. 1 – 26.

Ferris A. E., Shadbegian, R. J. and Wolverton, A. (2014) The effect of environmental regulation on power sector employment: phase I of the title IV SO₂ trading program, *Journal of the Association of Environmental and Resource Economics*, vol.1 pp. 521 – 553.

Golombek, R. and Raknerud, A. (1997) Do environmental standards harm manufacturing employment?, *The Scandinavian Journal of Economics*, vol.99(1) pp. 29 – 44.

Gray, W. B., Shadbegian, R. J. (2013) *Do the Job Effects of Regulation Differ with the Competitive Environment? Jobs and Regulation* edited by Cary Coglianese, Adam Finkel& Chris Carrigan, University of Pennsylvania Press.

Gray, W. B., Shadbegian, R. J., Wang, C. and Meral, M. (2014) Do EPA regulations affect labor demand? Evidence from the pulp and paper industry, *Journal of Environmental and Economic Management*, vol.68 pp. 188 – 202.

Gray, W. B. (2018) *Economic Costs and Consequences of Environmental Regulation*, London: Routledge.

Greenstone, M. (2002) The impact of environmental regulations on industrial activity: evidence from 1970 and 1977 Clean Air Act Amendments and the Census of Manufacturers, *Journal of Political Economy*, vol.110 p. 6.

Jaraite, J., Kazukauskas, A. and Lundgren, T. (2014) The effects of climate policy on environmental expenditure and investments: evidence from Sweden, *Journal of Environmental Economics and Policy*, vol.3(2) pp. 148 – 166.

Kahn, M. E. (1997) Particulate pollution trends in the United States, *Journal of Regional Science and Urban Economics*, vol.27(1) pp. 87 – 107.

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

Liu, M., Shadbegian, R. and Zhang, B. (2017) Does environmental regulation affect labor demand in China? Evidence from the textile printing and dyeing industry, *Journal of Environmental Economics and Management*, vol.86 pp. 277 – 294.

Morgenstern, R. D., Pizer, W. A. and Shih, J. (2001) The cost of environmental protection, *Review of Economics and Statistics*, vol.83(4) pp. 732 – 738.

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

Shadbegian, R. J. and Akofio-Sowah, N. (2001) *Does Environmental Regulation Affect Labor Demand? Evidence from US Manufacturing*, US Environmental Protection Agency.

United States Census Bureau (2008) *Comparing 2008 American Community Survey Data* [Online], Available from: <https://www.census.gov/programs-surveys/acs/guidance/comparing-acs-data/2008.html> [Accessed 7 January 2018].

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

Walker, W. R. (2013) The transitional costs of sectoral reallocation: evidence from the Clean Air Act and the workforce, *Quarterly Journal of Economics*, vol.128(4) pp. 1787 – 1835.

Appendix

$$\begin{aligned} \ln NPC_{it} = & \mathbf{D}_i + \mathbf{D}_t + \alpha_l \ln NP_{lit} + \alpha_e \ln NP_{eit} + \alpha_{i,l} \mathbf{D}_i \ln NP_{lit} + \alpha_{i,e} \mathbf{D}_i \ln NP_{eit} + \\ & \alpha_{t,l} \mathbf{D}_t \ln NP_{lit} + \alpha_{t,e} \mathbf{D}_t \ln NP_{eit} + \alpha_y \ln Y_{it} + \frac{1}{2} \beta_{yy} (\ln Y_{it})^2 + \frac{1}{2} \beta_{ll} (\ln NP_{lit})^2 + \\ & \frac{1}{2} \beta_{ee} (\ln NP_{eit})^2 + \beta_{le} \ln NP_{lit} \ln NP_{eit} + \beta_{yl} \ln Y_{it} \ln NP_{lit} + \beta_{ye} \ln Y_{it} \ln NP_{eit} + \\ & \beta_{tty} tt \ln Y_{it} \end{aligned} \quad (\text{A.1})$$

$$\begin{aligned} \ln NEMC_{it} = & \gamma_r \ln R_{it} + \gamma_l \ln NP_{lit} + \gamma_e \ln NP_{eit} + \frac{1}{2} \delta_{ll} (\ln NP_{lit})^2 + \\ & \frac{1}{2} \delta_{ee} (\ln NP_{eit})^2 + \delta_{le} \ln NP_{lit} \ln NP_{eit} + \delta_{ttl} tt \ln NP_{lit} + \delta_{tte} tt \ln NP_{eit} + \gamma_{tt} tt \end{aligned} \quad (\text{A.2})$$

$$\begin{aligned} v_l = & \left(\frac{EMC}{EMC+PC} \right) v_{l,R} + \left(1 - \frac{EMC}{EMC+PC} \right) v_{l,Y} = \left(\frac{EMC}{EMC+PC} \right) (\gamma_l + \delta_{ll} \ln NP_{lit} + \delta_{le} \ln NP_{eit} + \\ & \delta_{ttl} tt) + \left(1 - \frac{EMC}{EMC+PC} \right) (\alpha_l + \alpha_{i,l} \mathbf{D}_i + \alpha_{t,l} \mathbf{D}_t + \beta_{ll} \ln NP_{lit} + \beta_{le} \ln NP_{eit} + \beta_{ly} \ln Y_{it}) \end{aligned} \quad (\text{A.3})$$

$$\begin{aligned} v_e = & \left(\frac{EMC}{EMC+PC} \right) v_{e,R} + \left(1 - \frac{EMC}{EMC+PC} \right) v_{e,Y} = \left(\frac{EMC}{EMC+PC} \right) (\gamma_e + \delta_{el} \ln NP_{lit} + \\ & \delta_{ee} \ln NP_{eit} + \delta_{tte} tt) + \left(1 - \frac{EMC}{EMC+PC} \right) (\alpha_e + \alpha_{i,e} \mathbf{D}_i + \alpha_{t,e} \mathbf{D}_t + \beta_{el} \ln NP_{lit} + \\ & \beta_{ee} \ln NP_{eit} + \beta_{ey} \ln Y_{it}) \end{aligned} \quad (\text{A.4})$$

$$\sum \alpha_x = \sum \gamma_x = 1, \sum \beta_{yx} = \sum \beta_{xx} = \sum \delta_{xx} = 0 \text{ for } x \in \{l, k, e\}$$

$$v_l + v_k + v_e = 1$$

$$\text{constraints of } \ln PC : \begin{cases} \alpha_l + \alpha_k + \alpha_e = 1 \\ \beta_{yl} + \beta_{yk} + \beta_{ye} = 0 \\ \beta_{ll} + \beta_{kk} + \beta_{ee} + \beta_{le} + \beta_{lk} + \beta_{ke} = 0 \end{cases}$$

$$\text{constraints of } \ln RC : \begin{cases} \gamma_l + \gamma_k + \gamma_e = 1 \\ \delta_{ll} + \delta_{ee} + \delta_{kk} + \delta_{le} + \delta_{lk} + \delta_{ke} = 0 \end{cases}$$

NPC , $NEMC$, NP_l , and NP_e in equations A.1 – A.4 represent respectively normalized translog production cost function, normalized environment-related cost functions, normalized labor and energy prices. Iterative 3SLS estimator is used to estimate simultaneously a system of labor cost share (v_l) and energy cost share (v_e) while assuming cross-equation symmetry condition and homogeneity of degree one in input prices.

Table A.1. Parameter Estimates for Input Cost Shares

Sector	Basic iron and steel	Chemical	Electro	Food	Machinery	Motor vehicles	Pulp and paper	Rubber and plastic	Stone and mineral	Textile	Wood
α_t	0.58 (0.02)	0.66 (0.02)	0.96 (0.04)	0.88 (0.02)	0.93 (0.01)	1.18 (0.03)	0.53 (0.02)	0.82 (0.01)	0.92 (0.01)	0.76 (0.01)	0.84 (0.05)
α_e	0.32 (0.02)	0.23 (0.02)	0.06 (0.01)	0.02 (0.01)	0.01 (0.01)	0.01 (0.01)	0.18 (0.03)	0.12 (0.01)	0.02 (0.01)	0.08 (0.01)	0.08 (0.03)
β_{it}	0.15 (0.03)	0.09 (0.03)	0.04 (0.03)	0.12 (0.03)	0.06 (0.01)	0.01 (0.03)	0.14 (0.02)	0.08 (0.02)	0.09 (0.02)	0.07 (0.02)	0.06 (0.06)
β_{ee}	0.08 (0.02)	0.04 (0.02)	0.02 (0.01)	0.05 (0.01)	0.03 (0.01)	0.04 (0.01)	0.12 (0.01)	0.08 (0.01)	0.11 (0.02)	0.04 (0.01)	0.01 (0.01)
β_{te}	-0.07 (0.02)	-0.02 (0.02)	-0.02 (0.01)	-0.03 (0.01)	-0.03 (0.01)	-0.03 (0.01)	-0.07 (0.01)	-0.05 (0.01)	-0.09 (0.01)	-0.03 (0.01)	-0.02 (0.02)
β_{ty}	0.08 (0.01)	0.01 (0.01)	0.06 (0.01)	0.03 (0.01)	0.01 (0.01)	0.07 (0.01)	0.08 (0.01)	0.02 (0.01)	0.02 (0.01)	0.04 (0.01)	0.01 (0.03)
β_{ey}	-0.07 (0.01)	0.00 (0.01)	0.00 (0.00)	-0.03 (0.01)	0.00 (0.00)	-0.01 (0.00)	-0.06 (0.02)	-0.01 (0.01)	0.00 (0.01)	-0.01 (0.01)	0.01 (0.02)
γ_t	0.78 (0.24)	0.78 (0.18)	1.14 (0.52)	0.76 (0.12)	1.01 (0.24)	1.23 (0.38)	0.71 (0.07)	1.09 (0.31)	1.07 (0.21)	2.33 (0.28)	0.97 (0.44)
γ_e	0.18 (0.22)	0.26 (0.17)	0.49 (0.15)	0.03 (0.07)	0.33 (0.18)	0.15 (0.11)	0.27 (0.08)	-0.22 (0.22)	-0.30 (0.26)	-1.10 (0.20)	0.46 (0.21)
δ_{it}	-0.89 (0.44)	-0.41 (0.26)	3.87 (1.66)	-0.47 (0.22)	0.21 (0.15)	0.36 (0.79)	-0.01 (0.16)	0.72 (0.47)	0.22 (0.40)	1.45 (1.13)	0.18 (1.93)
δ_{ee}	-0.33 (0.33)	0.05 (0.16)	1.09 (0.30)	0.06 (0.12)	0.79 (0.17)	-0.08 (0.15)	0.02 (0.09)	0.40 (0.26)	0.31 (0.16)	0.90 (0.35)	0.00 (0.13)
δ_{te}	0.56 (0.32)	0.09 (0.15)	-0.93 (0.44)	-0.03 (0.10)	-0.17 (0.11)	0.27 (0.23)	0.07 (0.08)	-0.39 (0.25)	-0.17 (0.12)	-0.54 (0.52)	0.12 (0.22)
δ_{tlt}	0.02 (0.05)	-0.02 (0.03)	-0.13 (0.10)	0.00 (0.02)	-0.01 (0.03)	-0.06 (0.06)	-0.02 (0.01)	-0.07 (0.06)	-0.12 (0.03)	-0.21 (0.05)	0.02 (0.12)
δ_{tte}	0.03 (0.04)	-0.02 (0.03)	-0.10 (0.03)	0.00 (0.01)	-0.05 (0.02)	0.00 (0.02)	0.00 (0.01)	0.08 (0.04)	0.15 (0.03)	0.21 (0.04)	-0.08 (0.05)
Obs.	136	220	118	261	299	162	331	101	127	68	89

* Standard errors are provided in parenthesis.