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Environmental investment and firm performance: A panel VAR approach[1]

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Abstract

This paper analyzes the interactions between three dimensions of firm performance – productivity, energy efficiency, and environmental performance – and sheds light on the role of environmental investment. Environmental investments are efforts to reduce environmental impact, which may also affect firm competitiveness, in terms of change in productivity, and spur more (or less) efficient use of energy. We apply data envelopment analysis (DEA) technique to calculate the Malmquist firm performance indexes, and a panel vector auto-regression (VAR) methodology is utilized to investigate the dynamic and causal relationship between the three dimensions of firm performance and environmental investment. Main results show that energy efficiency and environmental performance are integrated, and energy efficiency and productivity positively reinforce each other, signifying the cost saving property of more efficient use of energy. Hence, increasing energy efficiency, as advocated in many of today's energy policies, would capture multiple benefits. The results also show that improved environmental performance and environmental investments constrain next period productivity, a result that would be in contrast with the Porter hypothesis and strategic corporate social responsibility; both concepts conveying the notion that environmental management can boost productivity.

JEL: D22, D24, M14, Q40, Q41

Keywords: Energy efficiency, Environmental investment, Environmental performance, Malmquist index, Panel VAR

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1. Introduction

Corporate environmental impacts have received increasing attention in the last decades, and the main focus has been on climate impacts and greenhouse gas emissions.[2] Alongside with the increasing societal environmental concerns, firms have also experienced increasing pressure from governmental environmental policy. Whether environmental policy can improve firms' competitiveness has been, and still remains, a debate since the Porter hypothesis was introduced in 1995 (see e.g. Brännlund et al., 1995; Porter and van der Linde, 1995; Jaffe and Palmer, 1997; Gray and Shadbegian, 2003; Hamamoto, 2006; Brännlund and Lundgren, 2010).[3] On the other hand, firms may go beyond compliance, take a proactive role in environmental protection (self-regulation), and implement so called corporate social responsibility (CSR). CSR can generally be considered as firms' strategic management aiming to meet societal expectations and minimize negative environmental impacts without compromising competitiveness.[4] In the last few decades, studies on whether CSR can contribute to firms' performance are flourishing, but evidence is not clear-cut.[5] In any case, whether performance is driven by regulation or self-regulation (CSR), understanding the relationships between firms' environmental investments and the actual economic and environmental and energy performances is crucial when evaluating the impacts of environmental management.

Swedish industry contributes to about 20% of GDP and is an important piece of the country's economic growth (Nauclér et al., 2012). The industry uses almost 40% of Sweden's final energy consumption. Although the energy use is mainly biofuels and electricity, fossil fuel still constitutes about 22% in 2011, and is responsible for 80% of the greenhouse gas emissions

[2] In Sweden, reducing climate impacts is listed in the first place among the 16 environmental quality objectives and the government is aiming for zero net emission in 2050 (Swedish Environmental Protection Agency, 2002).
[3] The Porter argument claims that there is a potential win-win solution of more stringent regulation. Supporters of this "no cost" policy paradigm, such as Cairncross (1992), Schmidheiny (1992), and Porter and van der Linde (1995), propose that firms need to change from the view that environmental management is an extra cost to a new and broader perspective that it could improve competitiveness and in the end even increase competitiveness. Opponents of this view, like Gray and Shadbegian (1993), Walley and Whitehead (1994), and Palmer et al. (1995) say that it is costly to be "green" and allocating resources to environmental management means sacrificing economic performance.
[4] A nice collection of papers regarding the economics of CSR can be found in McWilliams (2015). This collection examines the five related and most significant elements of this subject - theoretical perspectives, firm financial performance, socially responsible investing, environmental performance and strategic CSR – to provide a comprehensive exploration of the literature on CSR and its economic consequences.
[5] See discussions of motivations behind CSR and empirical evidence in e.g. McWilliams and Siegel (2000, 2001), Paul and Siegel (2006), Reinhardt et al. (2008), Margolis et al. (2009), Lundgren (2011), and Kitzmueller and Shimshack (2012).

(Swedish Energy Agency, 2013). Due to the important role the industry has in the economy, and for the environment, there is an increasing demand in society for responsible business practices (Bénabou and Tirole, 2003 and 2010; Besley and Ghatak, 2005).[6]

The aim of this paper is to estimate the relationships between firm performances in three dimensions - productivity, environmental performance, energy efficiency - and to evaluate the impacts of environmental investments. Here, environmental investment is defined as a firm's efforts to reduce its environmental impact, i.e., improving environmental performance, which may in turn affect the firm's competitiveness in terms of change in productivity and more (or less) efficient use of energy. We ground firm performance measurements in microeconomic production theory, and hence follow the advice of Paul and Siegel (2006) who are critical to the vast amount of studies using subjective CSR scores and financial performance rather than economic performance indexes (for this strand of literature, see overview in Margolis et al., 2009). We use Malmquist type of indexes of productivity, environmental performance, and energy efficiency, to measure firm performance. Then we carry out a second stage regression analysis to study the relationships between the firm performances and environmental investment. Recognizing that the Malmquist indexes are estimated rather than observed, and, as pointed out by Simar and Wilson (1999), that these indexes are biased,[7] we adopt Simar and Wilson (1999)'s bootstrap procedure to correct the estimated Malmquist indexes. Another objective of this study is to evaluate how the firm performances and environmental investment are causally interrelated. Does an increase in environmental performance follow an increase in productivity or vice versa? Is there, as you would expect, a positive interaction between environmental investment and environmental performance? Are environmental performance and energy efficiency positively related? In this study, we address our research questions taking into account properly the dynamic dimension, which is in line with e.g. Ambec et al. (2013) who argue that there is a lack of dynamic concern when assessing these relationships. To this end, in the second stage, we utilize a panel vector auto-regression (VAR) methodology: an econometric model that can examine the causal and dynamic relationships between the variables of interest, and can handle the inherent endogeneity problem present in our empirical application. In principle, all variables we are

[6] From a societal welfare point of view, it is desirable that environmental management strategies meet environment needs, and meanwhile maintain competitiveness.
[7] See detailed discussion of the lack of statistical underpinning of the calculated Malmquist indexes in Simar and Wilson (1999).

examining are endogenous to the firm and simple correlations or an empirical methodology that does not account for the endogeneity problem will generate results that are not statistically sound. The VAR method enables us to investigate the relationships between the three performances and environmental investments without explicitly having to specify a rigorous firm level, economic structural model.

The data-set used in the empirical analysis is a firm-level, industry-wide panel of Swedish manufacturing firms during the years 2002-2008. This data allows us to generate a deeper view of economic and environmental performance at the firm level, and enables us to estimate the relationships between firm performances and to evaluate specifically the impacts of environmental investments. To the best of our knowledge, this is the first study that uses a panel VAR approach to examine the causal and dynamic relationships of firm performances of this kind, and explicitly assess the role of environmental investment at the firm-level using an industry-wide collection of data.

The present study contributes to the literature in at least four respects. *i*) Firm performance is assessed in three dimensions on firm level – productivity (and its components), energy efficiency, and environmental performance. *ii*) The indexes that we use to measure performance are consistent in the sense that all are estimated using the Malmquist index approach, which is soundly grounded in production theory. *iii*) In exploring the relationships, we integrate the four variables of interest (including environmental investments) into a system of multiple, cross-sectional time series, and as such, our model allows for estimating the causal effects between all four variables, without requiring to, *a priori*, explicitly specify the causal directions. *iv*) We use a representative sample of firm-level, panel data consisting of 14 Swedish industry sectors, and thus our findings to a large extent are representative of the population of industrial firms as a whole, both in terms of environmental investments and firm performances.

The sum of the above contributions delivers unparalleled evidence on the covariation and causal relationships between different aspects of firm performance and environmental management, which adds novel and highly relevant empirical knowledge to the existing literature on environmental management and firm performance.

The rest of the paper is organized as follows. A brief selected review of previous literature is provided in the next section. Methodology is presented in Section 3. Section 4 describes data. Results and discussions are shown in Section 5. Section 6 concludes.

2. A selective literature review

The study is grounded in two streams of literature, both of which are by now huge in terms of number of studies; the Porter hypothesis and CSR. We first review studies on environmental investments or management and CSR, and their effects on firm performance. We then review studies on firm performance measurement and panel VAR.

2.1 Environmental investments, CSR, and firm performance

Studies on environmental investment or management and firm performance can be categorized into two genres. The first genre of these studies focus on assessing impacts of environmental regulation. The debate over the impact of environmental regulation/policy has been, and still remains a crucial subject matter since the Porter hypothesis was introduced. The Porter hypothesis claims that the right kind of stringent environmental regulation could induce firm innovation, increase efficiency, and ultimately improve productivity (Porter and van der Linde, 1995).

Some studies corroborate the Porter hypothesis. Dowell et al. (2000) investigate whether global corporate environmental standards would improve firm market value of a sample of U.S. multinational enterprises (MNEs). The sample data was drawn from the U.S. Standard and Poor's 500 list of corporations. The core result shows that firms that adopt more stringent global environmental standards have much higher market values (measured by Tobin's q). However they find that there is no lag effect of environmental standard on firm market value. Mohr (2002) uses a general equilibrium model of a closed economy to theoretically verify the feasibility of the Porter hypothesis. By imposing certain specific assumptions and conditions, the analysis finds that endogenous technical change makes the Porter effects possible, even though not necessarily optimal. Hamamoto (2006) uses sector-level data to estimate impacts of environmental regulation (measured by pollution control expenditures) in Japanese manufacturing 1971-1988. The results show that it has a positive direct impact on R&D expenditure and a positive indirect impact on total factor productivity growth. Harrington et al. (2009) find that the actual environmental regulation cost is lower than the estimated one in many occasions. This finding indicates that stringent environmental regulation might have a cost-reducing effect.

On the other hand, many studies have found weak or no Porter effects. Gray and Shadbegian (1993) calculate labor productivity and total factor productivity in US paper, oil and steel industries using reduced form linear models. By regressing calculated productivity scores on pollution abatement expenditures, the authors find that spending more on pollution abatement would result in lower production efficiency although regulatory inspection could reduce emission level. Walley and Whitehead (1994) challenge the notion that "stringent environmental regulation would enhance firm economic performance" and argue that improving environmental performance, e.g., by increasing environmental investments, comes at a cost and would actually hamper economic performance. Boyd and McClelland (1999) carry out a hyperbolic efficiency analysis in US integrated paper plants, and find that inputs and pollution could be reduced without decreasing productivity; however, environmental constraints reduce productivity. Boyd et al. (2002) calculate a Malmquist productivity index and an environmental performance index at plant level in US container glass industry, and find that productivity improvement and pollution reduction could exist simultaneously, but productivity losses occur after introducing emission control. Brännlund and Lundgren (2010) investigate the effects of carbon tax (a type of environmental regulation) in Swedish industrial firms between 1990 and 2004. They find a significant reversed Porter effect: both technological progress and profitability are negatively affected by the tax. Lundgren and Marklund (2014) calculate an environmental performance index and decompose it into policy and market driven, and estimate their impacts on profits in Swedish manufacturing. They find a positive effect of market driven environmental performance (which could be interpreted as CSR) on firm profit efficiency, while policy driven environmental performance has a neutral effect (the weak form of the Porter effect). Brännlund and Lundgren (2009) provide a comprehensive literature review on the topic of the Porter hypothesis. They find that there is no general empirical support for Porter hypothesis, and the validity of the Porter effects could only be affirmed by very special assumptions and conditions.

The second category of studies we review here focus mainly on examining the relationship between CSR and financial performance. A typical research question is: do socially responsible firms have higher financial performance? Examples of studies are, *inter alia*, Klassen and

McLaughlin (1996), Waddock and Graves (1997), Konar and Cohen (2001), Elsayed and Paton (2005), Scholtens (2008), and Nakamura (2011). Such studies typically define financial performance in terms of either stock prices or accounting profitability (e.g. return over assets), and social performance in terms of scores/ratings supplied by e.g. Kinder, Lydenberg, Domini Research & Analytics (KLD). In a fairly recent overview of these types of studies by Margolis et al. (2009) it is concluded that evidence is ambiguous but vaguely in favor of a small positive relationship between CSR and financial performance. However, causality is rarely (or never) accounted for appropriately in the empirical applications, and the scores/ratings seldom measure actual performances (see critical discussion about this in Paul and Siegel, 2006). This is something we try to address explicitly in our empirical analysis below.

The study most similar to ours is Bostian et al. (2015). They develop a network technology representation to measure energy efficiency, environmental performance and productivity change, while accounting explicitly for intertemporal investment decisions. The methodology is applied to a panel of Swedish manufacturing firms operating in the pulp and paper sector for the years 2002 - 2008, which is a subset of the data used in our application (one out of the 14 sectors we investigate). Our study diverts from that in the sense that we look at the whole manufacturing industry and focus specifically on dynamics and the cause and effect of firm performance and environmental investments.

2.2 Firm performance measurement and panel VAR

The Malmquist index has been used in a large number of studies to measure firm's productivity, energy efficiency, or environmental performance (e.g., Färe et al., 1986, Chambers et al., 1996, Boyd et al., 2002, and Ang, 2006). Previous studies typically measure and assess firm performance using a single index. In the present paper, we measure performance in three dimensions – productivity, energy efficiency, and environmental performance - and hence we need a method to analyze a system of multiple time-series in a cross-section of firms.

The vector autoregression (VAR) methodology treats all variables in a system of multiple time-series as endogenous and is thus appropriate to our empirical application. This technique was introduced by Sims (1980) and has been widely used primarily in macroeconomics. By allowing for unobserved individual heterogeneity, inherent in panel data, the panel VAR method, developed by Holtz-Eakin et al. (1988), has been utilized mainly in the literature of financial economics (e.g., Love and Ziccino, 2006, and Love and Ariss, 2014). So far, there is no panel VAR study that looks at the relationships between different firm performances and environmental management, which is the topic of this paper. To a very limited extent, our paper is related to Coad and Broekel (2012) that applies panel VAR to estimate the relationship between growths of employment, sales and productivity. Our study instead focuses on firm performance in terms of change in productivity, energy efficiency and environmental performance, and the role of environmental investments. Another relevant study is Jiang et al. (2015). They investigate the interaction between output efficiency and environmental efficiency of 137 firms in textile industry in China's Jiangsu province in the year 2009. They first use data envelopment analysis (DEA) method to calculate the efficiencies, and then use the structural equation modelling (SEM) to estimate the relationship. However, their study does not examine the dynamic linkage, and the causality is predetermined in the SEM model.

3. Methodology

3.1 The Malmquist indexes

Färe et al. (1989) define the Malmquist productivity index as a measure of productivity change of a decision making unit between two periods. We define Malmquist type of indexes for productivity, energy efficiency, and environmental performance. In constructing the first two indexes, productivity and energy efficiency, we use Shephard (1970) distance functions, which measure the radial distance of an output and input observation from itself to the best practice technology frontier. Let $y \in \Re_+^M$, $x \in \Re_+^N$ and $e \in \Re_+^P$ denote desirable outputs, non-energy inputs and energy inputs, respectively. Conceptually, the production technology can be defined as

$$T = \{(x,e,y): \ (x,e) \text{ can produce } y\}.$$

T is assumed to be closed and bounded. The output distance function is defined as

$$D_y(x,e,y) = \inf\{\beta : (x,e,y/\beta) \in T\}. \quad (1)$$

This distance function measures the output-oriented technical efficiency, i.e., the maximum percentage by which output y could be increased while still using the same input (x,e). The value of the distance function is positive in the range $(0,1]$. A higher value indicates higher technical efficiency.

Similarly, we can define the (energy) input distance function as

$$D_e(x,e,y) = \sup\{\beta : (x, e/\beta, y) \in T\}. \tag{2}$$

The distance function above contracts energy inputs while keeping outputs and non-energy inputs constant.[8] This distance function measures energy efficiency in the sense that how much energy could be maximally saved, while still producing the observed level of outputs, and using the observed level of non-energy inputs. The value of the distance function is positive in the range $[1,+\infty)$, and a higher value indicates lower energy efficiency.

Next, we follow Färe et al. (1986) and define the environmental distance function by using joint production framework in the presence of undesirable outputs. Let $y \in \Re_+^M$ and $b \in \Re_+^J$ denote desirable outputs and undesirable outputs, respectively. The joint production (environmental) technology can be defined as

$$\mathcal{T} = \{(x,e,y,b) : \ (x,e) \text{ can produce } (y,b)\}.$$

$\mathcal{T}$ is assumed to be closed and bounded. In addition, we impose the following properties on the technology (see, Färe et al., 1986).

i) Outputs are weakly disposable, implying that reduction of only undesirable outputs is not feasible, but proportional reduction of both desirable and undesirable outputs is feasible, i.e.

$$\text{if } (x,e,y,b) \in \mathcal{T} \text{ and } \theta \in [0,1], \text{ then } (x,e,\theta y,\theta b) \in \mathcal{T}.$$

ii) Good outputs are strongly disposable, implying that good outputs can be reduced freely, i.e.

$$\text{if } (x,e,y,b) \in \mathcal{T} \text{ and } y' \le y, \text{ then } (x,e,y',b) \in \mathcal{T}.$$

iii) Desirable and undesirable outputs are null-joint – no smoke without fire –, i.e.

$$\text{if } (x,e,y,b) \in \mathcal{T} \text{ and } b = 0, \text{ then } y = 0.$$

[8] By fixing non-energy inputs, we obtain a measure of pure technical energy efficiency.

Now we can define the environmental distance function following Tyteca (1997) as

$$D_b(x,e,y,b) = \sup\{\beta : (x,e,y,b/\beta) \in \mathcal{T}\}. \tag{3}$$

This distance function seeks to maximally contract undesirable outputs while holding inputs and desirable outputs unchanged. The distance function measures environmental efficiency in the sense that how much undesirable outputs could be reduced, while still producing the observed level of desirable outputs, without requiring additional amount of inputs. The value of the distance function is also positive in the range $[1, +\infty)$. A higher value implies lower environmental efficiency.

With the distance functions (1)-(3), we can construct a productivity index (*MP*), an energy efficiency index (*ME*), and an environmental performance index (*MEP*) as follows:

$$MP_t^{t+1} = \left[\frac{D_y^t(x^{t+1}, e^{t+1}, y^{t+1})}{D_y^t(x^t, e^t, y^t)} \times \frac{D_y^{t+1}(x^{t+1}, e^{t+1}, y^{t+1})}{D_y^{t+1}(x^t, e^t, y^t)} \right]^{1/2}, \tag{4}$$

$$ME_t^{t+1} = \left[\frac{D_e^t(x^t, e^t, y^t)}{D_e^t(x^{t+1}, e^{t+1}, y^{t+1})} \times \frac{D_e^{t+1}(x^t, e^t, y^t)}{D_e^{t+1}(x^{t+1}, e^{t+1}, y^{t+1})} \right]^{1/2}, \tag{5}$$

$$MEP_t^{t+1} = \left[\frac{D_b^t(x^t, e^t, y^t, b^t)}{D_b^t(x^{t+1}, e^{t+1}, y^{t+1}, b^{t+1})} \times \frac{D_b^{t+1}(x^t, e^t, y^t, b^t)}{D_b^{t+1}(x^{t+1}, e^{t+1}, y^{t+1}, b^{t+1})} \right]^{1/2}. \tag{6}$$

Here, $D^t(x^{t+1}, e^{t+1}, y^{t+1})$ is the distance function that the reference technology is constructed from data from period t and the data to be evaluated is from period $t+1$. Similarly, $D^{t+1}(x^t, e^t, y^t)$ is the distance function that the reference technology is constructed from data from period $t+1$ and the data to be evaluated is from period t. MP_t^{t+1}, ME_t^{t+1}, and MEP_t^{t+1} measures respectively changes of firm productivity, energy efficiency and environmental performance between periods t and $t+1$.

The values of all three indexes are non-negative. A value larger than 1 indicates progress of performance, a value smaller than 1 implies regress, and a value equal to 1 indicates no change.

3.2 DEA models for estimating distance functions

In the empirical applications, we can estimate the distance functions, $D^t(\bullet)$ and $D^{t+1}(\bullet)$ in (4)-(6), by using the data envelopment analysis (DEA) approach. It needs to compute for each index two within-period distance functions $D^t(t)$ and $D^{t+1}(t+1)$ and two mixed-period distance functions $D^t(t+1)$ and $D^{t+1}(t)$. There are $k=1,\ldots,K$ observations of inputs and outputs, (x^k, e^k, y^k, b^k), and we have two periods t and $t+1$. We want to estimate $D_y^t(x^{t+1}, e^{t+1}, y^{t+1})$ in (4), $D_e^t(x^{t+1}, e^{t+1}, y^{t+1})$ in (5), and $D_b^t(x^{t+1}, e^{t+1}, y^{t+1}, b^{t+1})$ in (6), for observation k'. By assuming that the technology is constant returns to scale, we can solve the following three linear programming problems.

$$
\begin{aligned}
\left(D_y^t(x_{k'}^{t+1}, e_{k'}^{t+1}, y_{k'}^{t+1})\right)^{-1} &= \max \beta \\
\text{s.t.} \quad & \sum_{k=1}^{K} z_k^t x_{kn}^t \le x_{k'N}^{t+1}, \quad n=1,\ldots,N, \\
& \sum_{k=1}^{K} z_k^t e_{kp}^t \le e_{k'p}^{t+1}, \quad p=1,\ldots,P, \\
& \sum_{k=1}^{K} z_k^t y_{km}^t \ge \beta y_{k'm}^{t+1}, \quad m=1,\ldots,M, \\
& z_k^t \ge 0, \quad k=1,\ldots,K.
\end{aligned} \tag{7}
$$

$$
\begin{aligned}
\left(D_e^t(x_{k'}^{t+1}, e_{k'}^{t+1}, y_{k'}^{t+1})\right)^{-1} &= \min \beta \\
\text{s.t.} \quad & \sum_{k=1}^{K} z_k^t x_{kn}^t \le x_{k'n}^{t+1}, \quad n=1,\ldots,N, \\
& \sum_{k=1}^{K} z_k^t e_{kp}^t \le \beta e_{k'p}^{t+1}, \quad p=1,\ldots,P, \\
& \sum_{k=1}^{K} z_k^t y_{km}^t \ge y_{k'm}^{t+1}, \quad m=1,\ldots,M, \\
& z_k^t \ge 0, \quad k=1,\ldots,K.
\end{aligned} \tag{8}
$$

$$\left(D_b^t(x_{k'}^{t+1}, e_{k'}^{t+1}, y_{k'}^{t+1}, b_{k'}^{t+1})\right)^{-1} = \min \beta$$

$$\begin{aligned} \text{s.t.} \quad & \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^{t+1}, \quad n = 1, \dots, N, \\ & \sum_{k=1}^{K} z_k^t e_{kp}^t \leq e_{k'p}^{t+1}, \quad p = 1, \dots, P, \\ & \sum_{k=1}^{K} z_k^t y_{km}^t \geq y_{k'm}^{t+1}, \quad m = 1, \dots, M, \\ & \sum_{k=1}^{K} z_k^t b_{kj}^t = \beta b_{k'j}^{t+1}, \quad j = 1, \dots, J, \\ & z_k^t \geq 0, \quad k = 1, \dots, K. \end{aligned} \tag{9}$$

In addition, the null-joint condition on technology $\mathcal{T}$ requires that the data satisfies two constraints: $\sum_{k=1}^{K} b_{kj} > 0,\ j = 1, \ldots, J,$ which says that each undesirable output is observed in at least one observation, and $\sum_{j=1}^{J} b_{kj} > 0, k = 1, \ldots, K$, which says that each observation produces at least one undesirable output.

In a similar way, the other three distance functions associated with each index can be estimated by changing the time subscripts in (7), (8), or (9).

3.3 The panel VAR model

We use a panel VAR methodology to investigate the relationships between firm performances and the impact of environmental investment. This approach allows that all the variables in a system of cross-sectional (multiple) time series can affect each other, and allows for the unobserved individual heterogeneity associated with panel data. Our panel VAR model consists of four equations:

$$MP_{kt} = \sum_{l=1}^{L} A_{11l} MP_{kt-l} + \sum_{l=1}^{L} A_{12l} ME_{kt-l} + \sum_{l=1}^{L} A_{13l} MEP_{kt-l} + \sum_{l=1}^{L} A_{14l} EI_{kt-l} + \lambda_{11} T + \lambda_{12} T^2 + f_{1k} + u_{1kt} \quad (10)$$

$$ME_{kt} = \sum_{l=1}^{L} A_{21l} MP_{kt-l} + \sum_{l=1}^{L} A_{22l} ME_{kt-l} + \sum_{l=1}^{L} A_{23l} MEP_{kt-l} + \sum_{l=1}^{L} A_{24l} EI_{kt-l} + \lambda_{21} T + \lambda_{22} T^2 + f_{2k} + u_{2kt} \quad (11)$$

$$MEP_{kt} = \sum_{l=1}^{L} A_{31l} MP_{kt-l} + \sum_{l=1}^{L} A_{32l} ME_{kt-l} + \sum_{l=1}^{L} A_{33l} MEP_{kt-l} + \sum_{l=1}^{L} A_{34l} EI_{kt-l} + \lambda_{31} T + \lambda_{32} T^2 + f_{3k} + u_{3kt} \quad (12)$$

$$EI_{kt} = \sum_{l=1}^{L} A_{41l} MP_{kt-l} + \sum_{l=1}^{L} A_{42l} ME_{kt-l} + \sum_{l=1}^{L} A_{43l} MEP_{kt-l} + \sum_{l=1}^{L} A_{44l} EI_{kt-l} + \lambda_{41} T + \lambda_{42} T^2 + f_{4k} + u_{4kt} \quad (13)$$

Here, MP_{kt}, ME_{kt} and MEP_{kt} are the DEA-estimated productivity index, energy efficiency index and environmental performance index of firm k at period t, respectively; EI_{kt} is environmental investment by firm k at period t. T and T^2 are linear and quadratic time trends, which are treated as exogenous. f_{1k}, f_{2k}, f_{3k} and f_{4k} are firm specific fixed effects; $u_{1kt}, u_{2kt}, u_{3kt}$ and u_{4kt} are disturbance error which has zero mean and variance $\sigma^2_{1kt}, \sigma^2_{2kt}, \sigma^2_{3kt}$ and σ^2_{4kt}, respectively.

We can use the system GMM method to estimate the coefficients in (10)-(13), but there are some issues we need to deal with. The first issue is that, the fixed effects are correlated with regressors since the lagged dependent variables are used as independent variables.[9] Thus, the standard fixed effects estimator (i.e., the first differencing procedure) is biased (Arellano and Bover, 1995). Additionally, the first differencing transformation could easily magnify gaps in an unbalanced panel (which we have). For example, if the value of y_{kt} is not available, then neither Δy_{kt} nor $\Delta y_{k,t-1}$ is available as well. We can use the Helmert procedure, or forward orthogonal deviation (FOD), to transform the data. This procedure takes away the mean of all available future observations of each unit, so it can retain more observations than the first differencing. In addition, the transformed regressors are still endogenous, i.e., the transformed regressors and disturbance terms are correlated. Using Helmert transformation enables the lagged variables to be

[9] In a panel VAR model, regressors on the right-hand side of each equation contain a lagged dependent variable.

independent of the transformed disturbances. Thus we can use the lagged variables as instrumental variables and construct the orthogonal condition necessary in the GMM estimation.

The lag length, L needs to be specified. It can be determined by using a model selection criteria; e.g., Akaike, Bayesian or Quasi information criteria, i.e., AIC, BIC and QIC. In the empirical application, we use the modified AIC, BIC and QIC suggested by Qu and Perron (2007) since these criteria can provide more robust test results, compared with the standard one.[10] The lag order that yields the smallest criteria values has been selected as preferred model.

Another issue is associated with the values of Malmquist index. As described in Section 3.1, the index value is always positive and a value equal to 1 implies that there is no performance change between two periods. If we directly use the estimated index values to estimate (10)-(13), the estimated coefficient of a lagged index variable is explained to be the impact of this variable when it has no change, i.e., when it is equal to 1, which may distort the estimation. To make it easy to interpret the estimated results, we subtract 1 from all the estimated Malmquist values. Thus, the index variables will have positive, zero, and negative values, where a value of 0 means that there is no performance change. The indexes are thus centered around 0 instead of 1.

The last concern is about the stochastic properties of the DEA-estimated Malmquist indexes. Since these Malmquist indexes are calculated deterministically by solving the distance functions and using equations (4), (5) and (6), they are not observed data generated from some stochastic process. According to Simar and Wilson (1999), these calculated indexes are biased and need to be corrected. We therefore adopt the Simar and Wilson (1999) bootstrap procedure to bias-correct our estimated Malmquist measurements and then use the corrected values in the panel VAR estimation.[11] The steps of the bootstrap procedure are:

1) Calculate the Malmquist indexes of productivity, energy efficiency and environmental performance using equations (4), (5) and (6).

[10] Qu and Perron (2007) pointed out that the AIC or BIC might underestimate the lag order when the sample size grows.

[11] Simar and Wilson (1999) present the bootstrap procedure for input-oriented Malmquist index. We trivially modify the procedure to fit the output-oriented Malmquist index. In the study, both energy efficiency, and environmental performance indexes are input-oriented

2) Use the bivariate kernel density estimation in Simar and Wilson (1999), and use the reflection method assuming the bandwidth $h=(4/5K)^{1/6}$ proposed by Silverman (1986), we can obtain a pseudo sample[12] $(x^{*t}_{kn}, e^{*t}_{kp}, y^{*t}_{km}, b^{*t}_{kj})$ for each observation of the original dataset to construct the reference bootstrap technology.

3) Calculate the bootstrap estimates of the Malmquist indexes using the pseudo sample in 2).

4) Repeat step 2) and 3) for B times (in this study we follow Simar and Wilson, 2000, and set B = 2000) to obtain B sets of estimates, $\widehat{MP}_{kt}^{t+1}$, $\widehat{ME}_{kt}^{t+1}$, $\widehat{MEP}_{kt}^{t+1}$, for each observation.

5) We can calculate the bias-corrected Malmquist indexes for each observation by using $\mathrm{M}^{*t+1}_{kt} = 2\times \mathrm{M}^{t+1}_{kt} - B^{-1}\sum_{b=1}^{B}\widehat{\mathrm{M}}^{t+1}_{kt}$, where $\mathrm{M} = MP, ME, MEP$.

However, as Simar and Wilson (1999) point out, a bias-corrected Malmquist index may yield higher variance than the original Malmquist estimate. Whether a Malmquist index needs to be corrected or not is an empirical question to be answered by the data in any given application. In empirical applications, the value of Malmquist index needs to be corrected when the condition $\left\{\widehat{\mathrm{M}}^{t+1}_{kt}\right\}_{b=1}^{B} < \frac{1}{3}(B^{-1}\sum_{b=1}^{B}\widehat{\mathrm{M}}^{t+1}_{kt} - \mathrm{M}^{t+1}_{kt})^2$, $\mathrm{M} = MP, ME, MEP$ is fulfilled. Therefore, we use step 5) to make a correction if this criterion is satisfied; otherwise, the original estimate of the Malmquist index is retained.

4. Policy context and data

4.1 Policy context for Swedish industrial firms

We are not explicitly taking into account any policy measures in our calculations or estimations, but there are reasons to believe that they are important for the behavior of firms, and thus the development of the estimated performance indexes and environmental investments. However, this study focuses on the inter-relationship between the variables of interest, and not on the

[12] In this pseudo sample, we only need to correct the observation vector which is the directional vector. For example, if we calculate productivity, only the output vector will be corrected whereas the input vectors are retained as original. See details in Simar and Wilson (1999), page 466.

factors that drive performances and environmental investments.[13] Nonetheless, below follows a brief description of the policy context of the industrial firms.

Sweden has a long history of taxing energy and emissions, and in 1990 - 1991 Sweden reformed its entire tax system, implementing taxes on energy, CO_2 and SO_2, as well as a fee on NO_x. The CO_2 tax gradually changed with more weight put on households and currently the industry pays only a part (about 20%) of the nominal tax rate. Other specific exemption rules apply to parts of the industry. In the period studied, 2002 - 2008, the main change in the policy arena is the introduction of the EU emissions trading system (EU ETS) in 2005. Studies show that the incentives for technological development induced by an EU price on carbon were not realized, most likely due to low permit prices (Lundgren et al., 2015). For the manufacturing industry within EU ETS, the CO2 tax was gradually phased-out from 2008, and completely removed from January 1, 2011. Sweden introduced the Energy Efficiency Improvement Program (PFE) in January of 2005 as an instrument to incentivize energy intensive firms to be more energy efficient. Firms can voluntarily join the program and be exempted from the energy tax. The first period of the program was concluded in 2009, and followed by a new five-year period. The effects of this program are disputed, but the Energy Agency claims energy savings of 1.4 TWh annually (www.energymyndigheten.se). However, in a study on Swedish forest industry firms, Blomberg et al. (2012) suggest that voluntary energy efficiency programs of this kind are more likely to be successful if explicitly targeted at promoting technological development.

4.2 Data

The empirical study is performed by using a sample of firm-level, industry-wide data from Swedish industry.[14] Data on the variables is collected and provided by Statistics Sweden (Statistiska Centralbyrån, SCB, www.scb.se). The unbalanced panel data set covers the years 2002 - 2008, and includes 14 sectors: pulp and paper, basic iron and steel, chemicals, mining, wood products, stone and mineral, food, motor vehicles, machinery, rubber and plastic, electro, fabricated metal products, textile, and printing. According to the definition of the Malmquist index, we select observations that are available for at least two consecutive years. Finally, the

[13] See e.g. Brännlund et al., 2014, or Jaraite et al., 2014, for an analysis of the effects of policy in the Swedish context.
[14] For a more complete description and discussion of this data, see Jaraite et al. (2014), who study a different problem but use data from same source.

data-set has 1966 observations and 517 firms. Descriptive statistics of the variables are presented in Table 1. All monetary values are in 2008 SEK.

Table 1. Descriptive statistics of variables by sector. Firm level, 2002-2008 (standard deviation in parentheses)

Sector	Output (MSEK)	Capital (MSEK)	Labor	Fossil fuel (GWh)	Non-fossil fuel (GWh)	Electricity (GWh)	CO2 (ton)	EI (SEK)	No. firms
PAP	2218	1886	757	165	312	702	44500	9442	43
	(2374)	(1934)	(823)	(280)	(353)	(951)	(45769)	(26508)	
BIS	2449	2176	1418	2030	23	287	697000	6283	12
	(2667)	(2681)	(1324)	(3740)	(46)	(312)	(1294946)	(11120)	
CHM	820	865	499	21	16	38	5141	1336	21
	(1538)	(1429)	(796)	(80)	(29)	(109)	(18780)	(2846)	
MIN	679	901	773	94	3	142	29160	7406	9
	(1758)	(2067)	(2203)	(289)	(12)	(421)	(90325)	(21809)	
WOD	386	135	152	3	44	18	790	791	113
	(722)	(258)	(260)	(9)	(74)	(32)	(2429)	(2303)	
STN	303	126	258	27	4	10	8436	1426	24
	(336)	(119)	(294)	(59)	(8)	(23)	(20611)	(4627)	
FOD	1185	430	557	23	5	27	5472	1243	58
	(2372)	(986)	(998)	(45)	(20)	(50)	(10899)	(3628)	
MOT	4502	1608	1451	19	8	51	5256	980	30
	(14195)	(4596)	(3459)	(45)	(17)	(102)	(13738)	(3070)	
MAC	908	201	494	2	4	14	593	410	100
	(1880)	(319)	(725)	(5)	(8)	(27)	(1150)	(1600)	
RUB	285	155	213	5	2	21	1346	396	13
	(392)	(163)	(473)	(10)	(5)	(24)	(2355)	(803)	
ELE	1393	153	523	3	2	12	850	540	31
	(2937)	(266)	(864)	(9)	(7)	(23)	(2490)	(1933)	
MET	49	32	67	1	0.6	5	330	2507	38
	(59)	(53)	(71)	(2)	(0.9)	(11)	(593)	(5310)	
TEX	28	12	42	0.3	0.6	0.7	76	0	4
	(55)	(94)	(75)	(2.8)	(2.1)	(1.2)	(125)	(0)	
PRN	86	118	157	4	2	3	970	365	21
	(93)	(121)	(219)	(7)	(5)	(6)	(1012)	(530)	

Note: EI= environmental investment; PAP= pulp and paper; BIS= basic iron and steel; CHM= chemical; STN= stone and mineral; MIN= mining; FOD= food; WOD= wood products; MOT= motor vehicles; MAC= machinery; RUB= rubber and plastic; ELE= electro; TEX= textile; MET= fabricated metal products; PRN= printing; MSEK=million Swedish Kronor; GWh=gigawatt-hours

Desirable output is calculated using firm's final sales divided by its corresponding sector-level producer price index. Non-energy inputs are capital stock and labor. Capital stock is obtained by using gross investment data and the perpetual inventory method.[15] Labor is the number of employees. Energy inputs are fossil fuel (coal, oil and gaseous fuel), non-fossil fuel (wood fuel

[15] For details on how the capital stock is calculated, see Brännlund and Lundgren, 2010.

and district heating) and electricity.[16] Undesirable output is carbon dioxide (CO_2) emission.[17] Statistics Sweden uses carbon emission factor to create the emission data, where wood fuel is assumed to be carbon neutral, and only the consumption of fossil fuels produces CO_2. Some industry firms use a significant quantity of biofuel as energy input, and the amount of CO_2 emissions from those firms may be a bit misleading. Instead of calculating ourselves the emissions from bioenergy, we have chosen to suffice with the official data.

The data-set contains data on investment in environmental protection. This covers treatment and prevention abatement investments on, for example, air pollution.[18] The treatment and prevention investments could be considered as reactive and proactive environmental investment respectively.[19] Ideally, we may treat each as an endogenous variable and examine the impact of reactive and proactive environmental investments on firm performance. However, due to data limitations, we have aggregated them into a single variable.[20]

5. Results

5.1 Estimation results of firm performance

We first calculate the Malmquist productivity, energy efficiency, and environmental performance indexes using (4), (5) and (6), respectively. The distance functions are obtained by solving (7)-(9) for each sector of each consecutive period. We then use the Simar and Wilson (1999) procedure illustrated in Section 3.3 to correct the estimated Malmquist indexes. Mean values of each index of two consecutive years of all sectors are shown in Table 2. Results show that mean performances exhibit some variation, but the overall trends are small. But this hides considerable

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[16] The original data base has six types of energy inputs, and there are many zeros in gaseous fuel, wood fuel and district heating, the DEA model used to calculate the Malmquist indexes has no feasible solution when we directly use six inputs of energy.

[17] The original data base also has SO_2 and NO_x emission data. However, since the amount of SO_2 and NO_x is nearly zero, and therefore, we only consider CO_2 as bad output in the empirical analysis.

[18] The environmental investment data covers the investment on water pollution, waste control, etc. Since our analysis treats carbon emission as the bad output, we therefore only include environmental investments associated with air pollution. See Jaraite et al. (2014) for a detailed description of the environmental investment data.

[19] The treatment investment does not affect the actual production process, whereas the prevention investment affects the production process (as described in Jaraite et al., 2014).

[20] Due to the administrative burden, Statistics Sweden collects environmental investment data only in firms having more than 50 employees since 2005. For firms that have fewer than 50 employees, this data is generated by using a certain statistical prediction method. To keep the consistency of our analysis, we take away firms with fewer than 50 employees from our data-set. They constitute about 20% of the total number of firms.

variation in the performances at the firm level (due to space considerations we leave out a more detailed presentation of firm or sector level results).

Table 2. Mean value of Malmquist indexes of all sectors

Periods	*MP*	*ME*	*MEP*
2001/2002	1.007	0.989	0.994
2002/2003	0.987	0.981	1.004
2003/2004	1.011	1.000	1.003
2004/2005	1.008	1.000	0.993
2005/2006	1.051	1.003	0.997
2006/2007	1.024	0.996	0.998
2007/2008	0.984	1.013	0.999
Average	1.010	0.997	0.998

We check the contemporaneous dependencies between firm performances and environmental investment by using a Pearson-type correlation test. Results (shown in Table 3) suggest that these four variables are related each other, as expected, except that the correlation between environmental investment and productivity/environmental performance is not significant. Nevertheless, environmental investment is positively correlated with energy efficiency at the 5% significant level. However, the magnitudes of the significant correlations are low. The dynamic relationships are expected to be more pronounced. Since this simple correlation test cannot identify the causal and dynamic relationships, we utilized a panel VAR model to investigate such relationships of our interested variables. Results are elaborated in the next section.

Table 3. Pearson-type correlation test between Malmquist indexes and environmental investment.

	MP	*ME*	*MEP*	*EI*
MP	1			
ME	0.378 (0.000)	1		
MEP	0.145 (0.000)	0.345 (0.000)	1	
EI	0.041 (0.120)	0.032 (0.023)	0.010 (0.731)	1

Note: p-values are in the parentheses

5.2 Estimation results of panel VAR

The panel VAR model is estimated by pooling the data from all sectors. The estimates describe the relationships between the firm performances and environmental investment of the entire industry. Fixed effects are included in the model to capture firm heterogeneity. We use a system

GMM method to estimate the coefficients of the system (10)-(13).[21] The values of the modified BIC/AIC/QIC are calculated by setting lag length *L* =1, 2, and 3. Results are shown in Table 4. The three criteria all have the lowest value when *L* is 1. Therefore, we select *L*=1 as the preferred lag length when we estimate the panel VAR(1) model.

Table 4. Lag order selection criteria

lag	MBIC	MAIC	MQIC
1	-179.236	-47.479	-100.958
2	-120.749	-33.911	-68.564
3	-64.156	-20.237	-38.064

Before we draw inference from the estimation results, it is necessary to check the stability of the estimated panel VAR(1) model; a stable model is invertible and can be represented in an infinite-order vector moving average (MA) representation. According to Hamilton (1994), a panel VAR model is stable, if the modulus of each eigenvalue is strictly less than 1.[22] Thus, we calculate the eigenvalue of (10)-(13). The corresponding values are 0.309, 0.294, 0.294, and 0.069, respectively. Thus, our model satisfies the stability condition.

We report the estimation results of the panel VAR(1) model in Table 5. The Sargan or Hansen test of over-identifying restrictions suggests that the instrumental variables used are valid instruments.[23]

[21] The STATA package pvar2 developed by Love and Ziccino (2006) is used to estimate the panel VAR. In order to obtain a robust variance estimates and adjust for cluster correlation, we use the Stata estimation command vce(bootstrap, cluster(varlist)). The vce(cluster) option will not affect the estimated coefficient. It adjusts the standard error and variance-covariance matrix of the estimators. See StataCorp (2013) for detail.

[22] The modulus of a complex number $x+iy$ is defined as $|x+iy| = \sqrt{x^2+y^2}$

[23] Lags 1 to 4 are used as instruments in our estimation.

Table 5. Estimation results of the panel VAR(1) model

	MP_t	ME_t	MEP_t	EI_t
MP_{t-1}	0.027	0.092***	0.010	0.028
ME_{t-1}	0.415**	-0.077	0.069**	0.274***
MEP_{t-1}	-2.054***	0.557***	0.293***	0.086
EI_{t-1}	-0.057**	0.012**	0.001	0.058
T	0.458**	0.151**	0.046***	0.025
T^2	-0.036**	-0.011**	-0.004**	-0.003

Sargan $\chi^2 = 52.644$ ($p = 0.299$)
No. of observations: 1966
No. of firms: 517

***, ** and * denotes 1%, 5% and 10% significant levels, respectively

The first row shows that previous period productivity growth generates positive impacts on all current firm performances and the environmental investment; however, it is only significant with respect to energy efficiency performance. This result indicates that previous period productivity enables firms to reduce energy consumption for a given output level in the next period. This result is similar to Boyd and Pang (2000) who illustrate that in US flat glass industry, a high productivity plant is associated with high energy efficiency. The result may also provide evidence which is opposite to the notion of "managerial opportunism" (see, e.g., Aklhafaji, 1989; Posner and Schmidt, 1992). Managerial opportunism advocates that in good times, managers prefer to seek short-term benefits, which would ultimately impede, e.g., energy/environmental performance and/or environmental investment. Our result, on the contrary, indicates that previous period productivity gain would facilitate the future energy efficiency, meaning the firm uses some of the gains to invest in energy saving equipment.

The second row shows that previous period energy efficiency growth has a significantly positive impact on current productivity, environmental performance, and environmental investment. One explanation for the positive impacts may be that increased energy efficiency would conserve resources, thereby contributing to the growth of productivity and environmental performance. And, furthermore, the conservation of energy resources may save costs, and therefore creates opportunity to increase the environmental investment. This result corroborates the narrative of multiple benefits of energy efficiency improvement in many of today's energy policies; and is consistent with the statement in, e.g., IEA (2015), that improving energy efficiency will accelerate productivity, increase profitability, alleviate environmental damage, and eventually urge an overall competitiveness. What's more, this result together with the result of the first row conveys a message that the productivity growth and energy efficiency gain could move forward hand-in-hand.

The third row shows that previous period environmental performance growth has a significantly positive impact on current energy efficiency growth and environmental performance itself. This means that improving environmental performance in one period would tend to boost future energy and environmental performance, and is likely to motivate more environmental investment in the next period. One explanation of the positive impact on energy efficiency improvement could be that, the previous period environmental performance improvement, either driven by technical progress (possibly induced by environmental policy/regulation) or cost saving concerns (such as cut carbon/energy tax payment), would lead to the mitigation of carbon emissions and thus reduce the fuel consumption. Moreover, the positive impact of environmental performance on energy efficiency, together with the positive impact of energy efficiency on environmental performance, implies that environmental performance and energy efficiency positively reinforce each other.

Results also suggest that previous environmental performance impedes current productivity. This means there is a trade-off between being environmentally friendly and productive performance. This result is what you would expect; resources are needed to enhance environmental performance, and the firm pays in terms of future productivity. Particularly, if the improvement of environmental performance is driven by environmental policy/regulation, this result does not support the "Porter Hypothesis", which says that the right kind of policy will spur innovation processes and technological development, and in the end, productivity or competiveness is improved. The rationale for our result is that in the short run, the (additional) cost of pollution control which is used to improve environmental performance is very likely to impair productivity growth and impede profit gain. This argument can be supported further by the statement in Porter and van der Linde (1995, p100): "*We readily admit that innovation cannot always completely offset the cost of compliance*[24]*, especially in the short term before learning can reduce the cost of innovation-based solutions*". This result is in line with a number of empirical studies, for example, Brännlund and Lundgren (2010) who find that the Swedish carbon tax has negatively affected the technological progress as well as profitability in Swedish industry during 1990 to 2004. It is also

[24] Here it would mean compliance cost to improve environmental performance.

consistent with Lanoie et al. (2008) who study a sample of 17 Quebec manufacturing sectors and find that strict environmental regulation in previous year would reduce productivity in the next year. There are a number of studies having found similar results with respect to environmental performance and economic performance (see, e.g., Gray and Shadbegian, 1993; Wally and Whitehead, 1994; Boyd and McClelland, 1999).

Alternatively, the mitigation of negative environmental externalities could also be induced by self-inflicted actions, such as implementing CSR. In this case, firms go beyond compliance and their managerial strategy adheres to a systematic approach that concentrates on conserving resources and promoting innovation (Hart, 1995). It has been argued that firms usually need quite a long period to capitalize on the costs of implementing CSR and promoting innovation (see, e.g., Russo and Fouts, 1997). Thus, it is reasonable to see the negative impact on the productivity growth, at least in the short run.

The fourth row shows that previous period increase in environmental investments has a significantly positive impact on the current energy efficiency gain, while the impact on productivity growth is significantly negative. This result suggests that expanding environmental investment would motivate energy efficiency improvement, but it may occupy resources and thus generates a barrier to spurring productivity growth. The significantly positive impact on energy efficiency improvement by increasing environmental investment, together with the significantly positive impact on environmental investment by improving energy efficiency, implies a positive interaction between them. Further, an increase in environmental investment has a positive but not significant impact on the current environmental performance, which is surprising. This is possibly because in such a short period (one year), environmental investment can hardly foster a significant environmental performance progress. Additionally, as Klassen and Whybark (1999) pointed out, environmental investment can improve environmental performance if a firm has an effective managerial strategy.

In order to formally examine causality, we run Granger causality hypothesis test, which can help us to determine if one time-series variable has the ability to forecast another and provides information of the causal direction (Granger, 1969). The test results are shown in Table 6. Dependent variables in the panel VAR(1) model are in the first column, and excluded lagged variables are in the second column.

Table 6 Wald test of Granger causality

		χ^2	df	$p > \chi^2$
MP				
	ME(*t*-1)	4.096	1	0.043
	MEP(*t*-1)	41.768	1	0.000
	EI(*t*-1)	5.867	1	0.015
	ALL(*t*-1)	47.266	3	0.000
ME				
	MP(*t*-1)	6.765	1	0.009
	MEP(*t*-1)	14.225	1	0.000
	EI(*t*-1)	4.562	1	0.033
	ALL(*t*-1)	33.366	3	0.000
MEP				
	MP(*t*-1)	1.803	1	0.179
	ME(*t*-1)	4.886	1	0.027
	EI(*t*-1)	0.023	1	0.880
	ALL(*t*-1)	6.789	3	0.079
EI				
	MP(*t*-1)	1.262	1	0.261
	ME(*t*-1)	9.562	1	0.002
	MEP(*t*-1)	0.536	1	0.464
	ALL(*t*-1)	14.781	3	0.002

H_0: Excluded variable does not Granger-cause Equation variable
H_1: Excluded variable Granger-causes Equation variable

From the results in the table, we can observe Granger causality relationship between almost all variables. Specifically, the previous productivity and energy efficiency can predict all future firm performances and environmental investment. Interestingly, previous period environmental performance or environmental investment could only forecast future energy performance. Also, as expected, the formal Granger tests confirm the estimation results in Table 5.

6. Summary and conclusion

This paper analyzes the dynamic and casual linkages between environmental investment and three dimensions of firm performance – productivity, energy efficiency and environmental performance. We ground our firm performance measurement in production theory and estimate Malmquist performance indexes. We carry out an empirical analysis using a firm-level, industry-wide panel data-set from Swedish industry for the period 2002 - 2008. To investigate the causal and dynamic relationships, we adopt a panel VAR approach which can treat all the variables in the system as endogenous and allow for unobserved individual heterogeneity associated with panel data. Simar and Wilson (1999)'s bootstrap procedure is adapted to bias-correct the estimated Malmquist indexes.

Results indicate that environmental performance and energy efficiency are integrated, which is not surprising. That is, previous period progress in environmental performance has a positive impact on current energy efficiency, and vice versa. Further, previous increase in environmental investment induces current energy efficiency improvement, signifying that such investments may primarily be directed towards conserving energy use.

We also note that previous period energy efficiency seems to facilitate current productivity growth, emphasizing the potential cost saving value of energy conservation. Moreover, we also find that previous period productivity growth promotes current energy efficiency improvement, suggesting even further that energy efficiency and productivity are positively related.

We now turn to a central result. Increasing previous period environmental performance and/or environmental investment constrains current growth of productivity. This would suggest that efforts to mitigate the environmental burden of the firm – either driven by environmental regulation or by self-induced CSR – are not free, in the sense that it puts a burden on productivity growth in the next period. Particularly, if the improvement of environmental performance and the increase in environmental investment are induced by environmental regulation, our result does not corroborate the Porter argument. Performance improvement and/or the investment spurred by stricter regulation will cause a scarcity of resources for productive use.

Productivity growthin previous period may potentially boost current environmental performance and environmental investment, suggesting that some of the gains from production are used for environmental management. This result shows opposite evidence to the behavior that has been coined "managerial opportunism" (Posner and Schmidt, 1992), i.e., using productivity gains for short-term gains. Our result, by contrast, suggests that in good times, managers show what we could coin "managerial environmentalism"; productivity gains are invested in more long-term projects that reduce environmental impact.

Finally, we find that an increase of previous period environmental investment improves current energy efficiency, and in turn the improved energy efficiency will tend to increase productivity, environmental performance and environmental investment in the next period. As a consequence, this suggests that it is possible to plan an effective environmental investment strategy which could boost productivity, if channeled via a cost saving energy efficiency improvement.

In terms of energy efficiency and environmental performance our results tell two stories.

On the one hand, the results indicate that firms that improve energy efficiency are likely to start a positive chain of events, which would facilitate productivity, reduce environmental load, induce environmental investment, and, as an effect, possibly lessen carbon tax burden and enhance market reputation. From a strategic management perspective, this implies that firms should seek to improve energy efficiency.

On the other hand, whether environmental performance is induced by regulation or self-regulation, our result shows that it directly causes productivity loss. From a policy aspect, this denotes that the 'win-win' outcome which has been posited by Porter and van der Linde (1995) can hardly be realized.

The discussions above and the implications drawn in this study are placed in the context of Swedish industry. It will be appealing to broaden future studies to all sectors of the economy and longer sample period, which could provide a more comprehensive analysis of the long-term relationship between environmental behavior and economic performance. Future research direction should also consider explicitly including policy measurements, to the extent they are available and reliable.

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