Energy Economics 57 (2016) 243–255

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneco

Environmental investment and firm performance: A network approach

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ARTICLE INFO

Article history:
Received 20 September 2015
Received in revised form 10 May 2016
Accepted 30 May 2016
Available online 10 June 2016

JEL classification:
Q40
Q52
Q55

Keywords:
Energy efficiency
Environmental performance
Network DEA
Malmquist index
Investment

ABSTRACT

This study examines the role of investment in environmental production practices for both environmental performance and energy efficiency over time. We employ a network DEA approach that links successive production technologies through intertemporal investment decisions with a period by period estimation. This allows us to estimate energy efficiency and environmental performance separately, as well as productivity change and its associated decompositions into efficiency change and technology change. Incorporating a network model also allows us to account for both short-term environmental management practices and long-term environmental investments in each of our productivity measures. We apply this framework to a panel of detailed plant-level production data for Swedish manufacturing firms covering the years 2002–2008.

1. Introduction

Investment in new technology serves as one important way for firms to reduce their energy use and pollution emissions in response to more stringent climate policies. This form of investment, which we refer to as *environmental investment*, has the potential to drive technological change, both directly through design improvements, and indirectly through spillover effects (Clarke et al., 2006, Fischer and Newell, 2008). When this potential exists, it is likely optimal for climate policies to couple emissions taxes with environmental investment incentives (Acemoglu et al., 2012). In addition to lowering the costs of emissions reductions over time, environmental investment-driven technological change can also lead to overall increases to firm productivity and profits, commonly known as the Porter hypothesis (Porter and van der Linde, 1995).[1] The corporate social responsibility literature finds a similar potential for increased competitiveness resulting from environmental investments (Kitzmueller and Shimshack, 2012).

In light of this, it is important to incorporate environmental investment and environmental management decisions into technology models that measure production performance, both in terms of conventional productivity and its components, as well as in terms of environmental performance and energy efficiency. Namely, all investments are not the same. As opposed to conventional, production-oriented investments, environmental investments are primarily intended to reduce pollution. In a multi-input, multi-output production context, the mix of investment inputs, rather than simply the total quantity, matters in shaping the feasible mix of pollution and production outputs. For instance, a greater intensity of environmental investment could shift the technology so that a given level of production is possible with lower emissions, while a greater intensity of production-oriented investment may shift the technology towards both increased production and increased emissions. Thus, pooling these different forms of investment in a production modeling framework could lead to biased performance estimates, for both emissions and production objectives, and distort estimates of the associated tradeoffs for reducing emissions. This makes a greater understanding of the role of environmental investment in firm performance particularly important for designing policy incentives for environmental R&D, which are commonly included in climate policy proposals (Newell, 2007, Popp and Newell, 2012).

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[1] For a review on theory and empirics related to the Porter hypothesis see Brännlund and Lundgren (2009).

http://dx.doi.org/10.1016/j.eneco.2016.05.013
0140-9883/

In addition, including environmental investment separately could help to better understand the degree to which complementarities or substitutions between different forms of investment exist. For instance, replacing outdated equipment with newer, more efficient models that happen to use less energy has the added benefit of reducing emissions from fossil fuels. On the other hand, there is also evidence that environmental investments can lead to crowding out of other investments (Popp, 2006, Popp and Newell, 2012).

Finally, environmental decisions extend over different time scales. While short term management practices largely depend on existing technologies, investment decisions are made over longer time horizons and likely contribute to technological change (Clarke et al., 2006, Fischer and Newell, 2008). To account for the intertemporal nature of investment decisions, we link previous investments to current production as part of a network representation of the production technology, in order to gauge performance along each of the three dimensions.

We take an index approach to measure each aspect of performance, jointly accounting for environmental and production-oriented investments, environmental expenditures, emissions and energy use. Our approach draws on the use of Malmquist quantity indexes to measure environmental performance as presented in Färe et al. (2004) and the more recent extension to panel data presented in Färe et al. (2006, 2010). This paper also adds to the growing use of productivity theory-driven methods to measure energy efficiency and environmental performance (Jaraite and Di Maria, 2012, Wu et al., 2012, Zhang et al., 2013, Zhou et al., 2010). To the best of our knowledge, this study represents the first extension of this framework to include intertemporal environmental investment decisions.

We introduce firm-level investments, both environmental and production oriented, into a Data Envelopment Analysis (DEA) (Charnes et al., 1978) representation of the production technology. We connect successive production technologies over time using network DEA methods to better understand how investment enters into productivity, energy efficiency and environmental performance. Network DEA models connect separate but related production processes to measure the efficiency of the system, better accounting for its internal structure (Kao, 2014). Common network DEA applications include supply chain management and transportation efficiency. There is now a considerable literature on the use of DEA methods to model environmental and energy technologies (Zhou et al., 2008b), much of which focuses on methods to model undesirable outputs such as pollution emissions as part of an economic production process. However, only a handful of studies adopt network or multi-stage modeling frameworks to represent the production process for emissions and estimate environmental performance.

Murty et al. (2012) develop a bi-production framework that decomposes the overall technology into a standard intended production technology and a residual-generation technology for inputs that directly contribute to pollution, such as the use of fossil fuels or abatement activities. Färe et al. (2013) break the technology into two stages. In the first, firms use inputs to jointly produce good and bad outputs, and then in the second stage, they use inputs for abatement. In their framework, some of the good and bad outputs from the first stage serve as intermediate inputs in the abatement stage, so that the problem becomes to solve for the optimal allocation of intermediate inputs, along with other exogenous inputs, between stages of production. Hampf (2014) incorporates a materials balance condition into a similar two-stage network and proposes a measure of environmental efficiency as the product of production efficiency and abatement efficiency.

This study contributes to the nascent use of network approaches to model environmental production processes by connecting the technologies for good and bad outputs through intertemporal investment decisions. We consider both energy efficiency, in terms of energy used in production, and environmental performance, in terms of emissions, as well as overall productivity change, for a panel of Swedish manufacturing firms in the pulp and paper sector for the years 2002–2008. Working with detailed production data at the firm level allows us to examine environmental investments separately from production-oriented investments, and to distinguish longer term environmental investments from annual environmental management expenditures. Following Jaraite et al. (2014), we categorize investments and expenditures for Swedish manufacturing. Environmental investments include both pollution treatment, or 'end-of-pipe' techniques (e.g., air filters and scrubbers), and pollution prevention processes (e.g., fuel switching/saving equipment and re-circulation of process gases); environmental expenditures include operating costs of existing environmental equipment, internal monitoring, personnel training, and remediation costs. Our data also include information on energy use and emissions of CO_2, SO_2, and NO_X.

Modeling these factors separately provides additional insight that could be of practical use, from both a policy and a managerial perspective. For instance, policy incentives for emissions reductions, such as emissions taxes or permit systems, may pose additional costs if ensuing environmental investments crowd out productive investments (Gray and Shadbegian, 1998, Kneller and Manderson, 2012). On the other hand, emissions policies may also promote energy efficiency objectives if they induce firms to invest in fuel-saving production processes or substitute other inputs for energy use (Orlov et al., 2013). Likewise, incentives to increase energy efficiency, such as fuel taxes or subsidies for R&D, can also lead to investments in emissions reductions (Hammar and Löfgren, 2010, Löfgren et al., 2008, Triguero et al., 2014).

We introduce our environmental investment network technology in the next section, and then explain how we use this framework to construct index measures for energy efficiency, environmental performance and productivity change in Section 3. We present our application to Swedish pulp and paper production in Section 4.

2. Modeling framework

We take an axiomatic approach to modeling the production technology, similar to previous studies incorporating network methods for environmental technologies (Färe et al., 2013, Hampf, 2014, Murty et al., 2012). This allows us to build our performance indexes from distance functions, which because they are estimated solely from quantity data, enable us to incorporate emissions into our performance measures without requiring price information on the associated damage costs. The resulting performance indexes, constructed from ratios of distance functions, also satisfy a number of desirable properties from index theory (Färe et al., 2010). We use DEA methods to estimate the associated distance functions empirically. DEA offers several advantages in practice. Perhaps most important of these is the ability to explicitly impose the key axiomatic properties from production theory (Convexity, Compactness, Completeness) non-parametrically, without having to assume a functional form for the production relationship. DEA is also straightforward to implement and facilitates a variety of index decomposition techniques. This more directly connects our indexes to an extensive literature on the use of DEA to estimate environmental performance and energy efficiency (Zhou et al., 2008b).

Arguably the primary limitation of DEA is the deterministic nature of frontier estimates, which attribute distance from the frontier solely to inefficiency. The main alternative to DEA is to use stochastic frontier analysis (SFA) methods, which incorporate an error structure into distance function estimates. One important advantage of SFA methods in our case, working with a panel data set, would be the ability to better account for unobserved heterogeneity across firms. For instance, Kopsakangas-Savolainen and Svento (2011) find that unobserved heterogeneity can substantially bias inefficiency estimates and alter performance rank order. Given our focus on index