Australian Government
Department of Industry, Innovation and Science
Office of the Chief Economist

RESEARCH PAPER 5/2016

Clean Technology, Regulation and Government Intervention: The Australian Experience

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February 2017

Abstract

This study assesses the impact of an Australian grant programme that supported manufacturing businesses to invest in energy efficient equipment, technologies, processes and products. A production function approach is used to isolate and examine the portion of emission change linked to technological shift. It also tests whether exposure to facilities that receive the grant encourages the adoption of clean technology elsewhere.Overall, there has been about a 10 per cent reduction in emissions due to a sector-wide shift to cleaner technologies from 2011 to 2014. The effect of the grant programme is size dependent, and small and very large facilities mainly invested to reduce emission intensity beyond the average. The exposure to the programme mostly affects firms where production is geographically concentrated.

JEL Codes: D22, H23, L6, Q54
Keywords: Emission, Technology Adoption, Climate Change, Public Policy

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Key points

- From 2011 to 2014, there has been a 10 per cent drop in manufacturing emissions as a result of facilities switching to cleaner technologies.
- Simultaneously, manufacturing emissions increased by about 6 per cent as a result of an increase in energy consumption.
- Facilities that benefited from the CleanTech programme also reduced their emissions substantially, but not necessarily through technology adoption.
- Exposure to CleanTech projects mostly affected facilities belonging to firms where operation is geographically concentrated.

1. Introduction

In 2011, Australia introduced a Clean Energy Future Plan (Clean Energy Act, 2011). One element of the plan was a Clean Technology Investment Fund (codenamed CleanTech). This programme, which ran from 2012 to 2014, offered financial grants to manufacturing facilities to switch to cleaner technologies. It was intended to allow facilities to retain their competitiveness relative to international competitors that might not be burdened by climate-related regulations. One would expect larger investment in clean technology and more emission reduction among these facilities. I study whether this has been the case. I also study whether the characteristics of the CleanTech facilities had any implications in how they used the grants.

Finally, using a few measures of exposure to CleanTech, I test whether CleanTech projects had any broader impact by influencing the technological shift in other facilities that are either part of the same parent firm or geographically co-located.

These research questions are of importance in policy design. Reduction in emissions can be achieved by cutting business activity or by adopting cleaner technology. The former is a myopic strategy and has adverse economic consequences. The latter is a long-term and desirable outcome. It is important to know what portion of emission reduction is of the desired nature.

Also, the CleanTech programme came with a price tag of almost half a billion dollars for the government. The scale of the programme demands some justification in terms of added benefits and impact.

To answer these questions, I model the emission technology as a production function with time-varying parameters. The function takes energy consumption as input and generates emission as output. The change in emission between two time points can be decomposed into the change in energy consumption keeping technology fixed plus the change in technology keeping energy consumption fixed. A log-linear specification develops that can be estimated by Ordinary Least Squares (OLS). I then use the estimated coefficients to predict the contribution of each factor in reducing emissions within a facility with a special focus on the role of technological shift.

I find about 10 per cent drop in the manufacturing emissions directly associated with a change in technology. The technological effect of CleanTech has been size-dependent, with size measured in energy consumption. Specifically, small and large facilities made larger investments in clean technology. Other CleanTech facilities seem to have invested in reducing energy intensity – i.e. energy consumed per unit of business activity – in larger proportions.[1]

I also find that the impact of CleanTech has been very localised and lacks any diffusive nature even across facilities belonging to the same parent firm. Only firms with centralised operation exhibit some extra reduction in electricity consumption as a result of being exposed to CleanTech.

The rest of this paper is composed as such: The next section provides a short background on the topic. In Section 3, I introduce the sources of data used for

[1] In fact, some CleanTech projects are about switching to LED lighting or using controls to automatically shut down electrical devices during periods of inactivity.

the study. In Section 4, I describe the production function approach and derive the structural equation to be estimated. Section 5 presents the estimation results. Section 6 presents estimation results pertaining to the exposure effects. The paper is concluded in Section 7.

2. Background

Urging reduction in carbon emissions while counting the economic cost of switching to cleaner technology has been part of a long standing policy debate (See Nordhaus & Boyer, 1999; Stern, 2008; Tol, 2009, for instance). Governments in different countries have adopted a combination of regulation and taxation together with subsidies and assistance programmes to accelerate the move to cleaner technologies while reducing the cost to private companies of compliance (Andrews, 1994).

The European Union's ETS started in 2005 and is one of the largest in coverage and longest running scheme in the world. It is a cap and trading scheme, that is, it sets an overall limit on emissions in the EU and then issues permits within the cap. These permits are allocated to emitters through an auctioning mechanism. The EU ETS has a preferential nature and provides greater exemptions and free allocations to members with weaker economies.

The initial report of verified emissions for the EU in 2007 shows a mixed pattern amongst the members (EC, 2008). The total emission increased by 0.68 per cent during this period, adjusting for the change in the number of facilities covered. In the years that follow, there is a varying pattern of emission increasing in some years and decreasing in the others.

In 2011, the Australian government followed a similar path by the introduction of Clean Energy Future Plan (Clean Energy Act, 2011). The centrepiece of this policy was a carbon pricing scheme that came into effect in July 2012. It coincided with the commencement of the Australia's commitment under the Kyoto protocol. Under this scheme, emission producers had to pay a set price for each tonne of carbon emission or the equivalent (Jotzo, 2012). The scheme and the CleanTech programme were later repealed in July 2014.

A few studies so far have quantified the emission reduction during this period. O'Gorman & Jotzo (2014) estimate an 8.2 per cent reduction in the emissions generated by the electricity sector over this period. A recent report by the Australian Department of Environment points to similar evidence (NGGI, 2015).

The existing evidence, however, does not document whether these emission reductions are achieved through the adoption of cleaner technologies. In this work, I provide some evidence on the manufacturing sector and make distinction between the emission reduction caused by change in energy consumption and that caused by technological shift to assess the impact of the CleanTech programme.

3. Data

This study is based on a matched dataset that uses National Greenhouse and Emission Reporting Scheme (NGERS) data from the Australian Clean Energy Regulator in conjunction with the CleanTech programme data from the

Department of Industry, Innovation and Science. In what follows, I will separately introduce these databases and then describe the matching process.

3.1 NGERS

The National Greenhouse and Emission Reporting Scheme Act of 2007 (coming into effect in 2008) was introduced by the Australian Government in part to fulfil Australia's international obligations (See NGER Act, 2007, for details). It is also an initiative to collect data that would help in the design of policies targeting emission reduction and climate change. The thresholds for obligatory reporting have been gradually lowered since the inception of the Act. As of 2010, firms or entities meeting either of the following annual thresholds are obligated under the legislation to report into NGERS (NGER Act, 2007, Part 2 Section 13):

a) total amount of greenhouse gases emitted from the operations of facilities under the operational control of entity is 50 kilotonnes or more; or

b) total amount of energy produced from the operations of facilities under the operational control of entity is 200 terajoules or more; or

c) total amount of energy consumed from the operations of facilities under the operational control of entity is 200 terajoules or more.

A facility within this context is basically a plant, location or establishment with the possibility of being part of a larger multi-facility parent firm.

The NGERS requires that the reporting firms record their energy consumptions and CO_2 equivalent emissions by activity in each facility that they control. The general class of activities reported in NGERS are those releasing emission as a result of (a) energy production, (b) fuel combustion, (c) fugitive emissions, (d) industrial processes, (e) scope 2 energy consumption (see below), or (f) waste handling. Facilities in practice undertake multiple activities internally, each reported separately, and each firm has the potential to own and control multiple facilities in various locations.

The NGERS, in particular, is detailed about the type of emissions produced by classifying each activity as either

Scope 1: emission and energy usage as a result of on-site energy conversion; or

Scope 2: purchased energy (such as electricity) and the associated indirect emissions.

In case the facility is using energy from renewable sources, it reports the energy consumption from that source and records zero emissions associated with it (see Appendix A for a sample). Total energy usage and emission by a facility in a year are the ones summed over all activities and mix of sources reported for that facility.

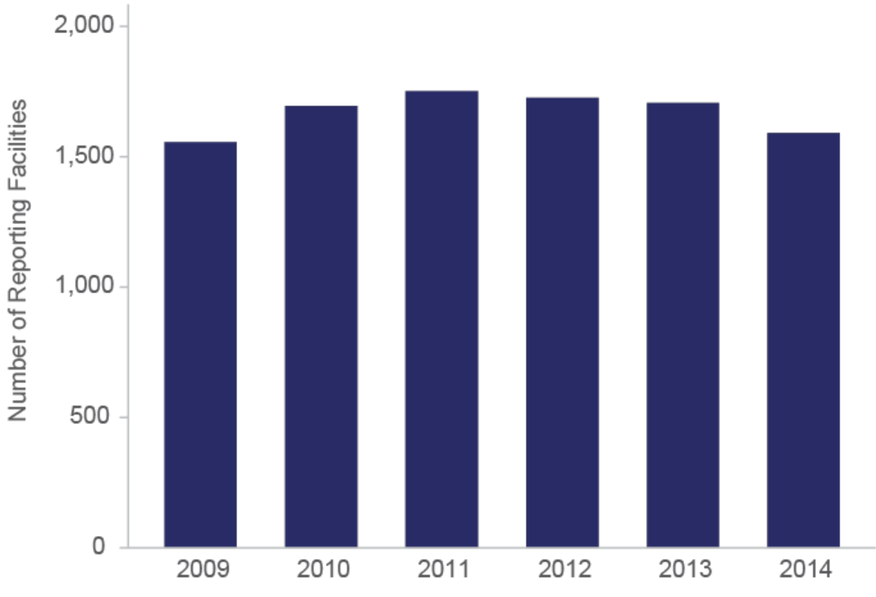
Firms also report the number of operation days for which emission and energy is recorded. The majority of facilities report for 365 days. To make the reports uniform, I use this information to proportionally inflate the remaining values to a 365-day operation, assuming that the operation is uniformly distributed across every day.

Most facilities in the data are geo-coded and come with their longitude and latitude coordinates, making exact positioning possible. Finally, each facility is reported with the industry classification code pertaining to its activities regardless of the industry of the parent firm. The data is confidential and is available by authorisation from the Australian Clean Energy Regulator.[2]

For my study, I am using the Section 19 activity report of the NGERS. Since CleanTech investment grants are offered to manufacturing activities only, I also restrict my data to manufacturing facilities. The data encompasses about 1,700 manufacturing facilities per year being controlled by close to 250 parent companies (Figure 1). The firms reporting into NGERS are split between single-facility firms and multi-facility parents, and since 2010 about two-thirds of all firms reporting into NGERS have been multi-facility.

Figure 1: The count of facilities and firms reporting into NGERS over the years

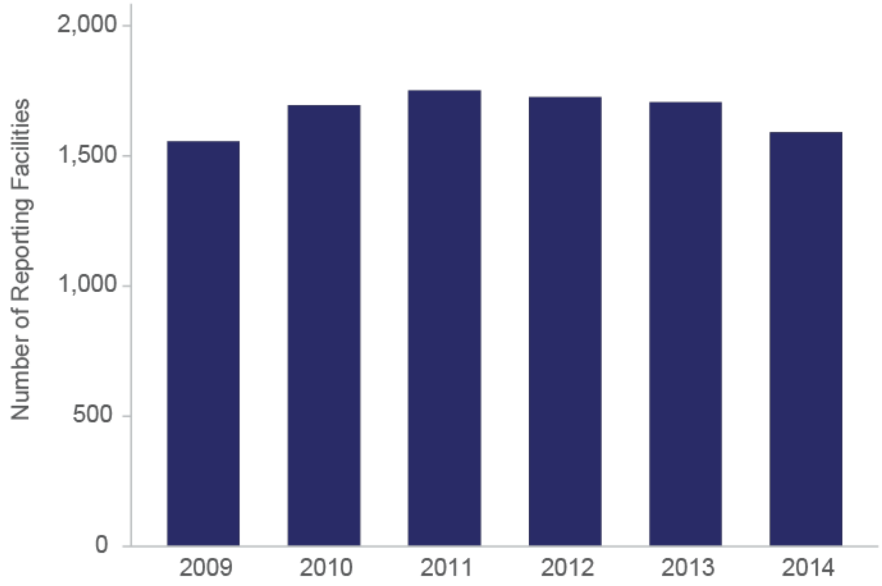
a) Facilities



(b) Firms

[2] See http://www.cleanenergyregulator.gov.au/

a) Facilities



Source: NGERS database

3.2 CleanTech

In 2012, the Australian Government introduced the Clean Technology Investment Programme (or CleanTech) as part of Clean Energy Act (2011). The programme assists Australian manufacturing businesses to maintain competitiveness in domestic and international markets while reducing their carbon emissions by switching to more efficient and cleaner capital equipment and technologies.[3] The programme offered grants of up to half the estimated

[3] See https://www.business.gov.au/assistance/clean-technology-investment-programme for details.

cost of the proposed projects. The last applications for this grant were accepted in 2014. The programme has three components:

Innovation Programme: Grants for research and innovation in the field of clean energy (about $28 million for 28 projects).

Investment Programme: Grants to facilitate switching to cleaner technology (about $250 million for 232 projects).

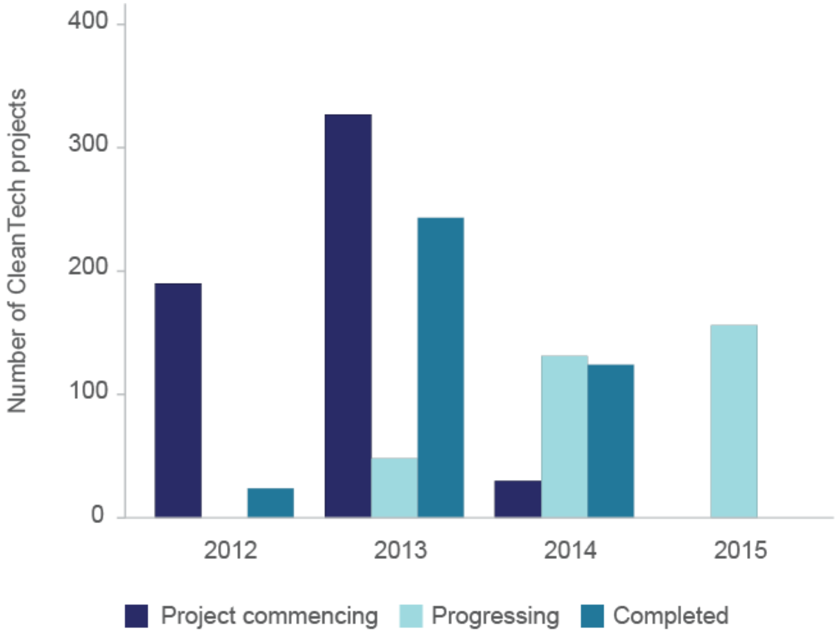
Food and Foundries Investment Programme: Almost half of the overall budget for the investment grants was dedicated to food manufacturing and foundries due to special demand (about $250 million for 315 projects).

The last two types of grants were only offered to manufacturing activities.

The Australian government keeps an administrative database of the CleanTech projects which is regularly updated by registrant reports. The database keeps the government abreast of the progress in each project and for post-project evaluations. Some details of the database, such as business contacts, are confidential whereas the rest of the information is posted publicly.[4] For this study, I am given access to the confidential database.

In this study, I am focusing on the role of this programme in reducing emission intensity. Therefore, I will restrict myself to Investment and Food and Foundry projects. By 2015, 391 investment projects have finished, while 156 are still in progress but expected to conclude soon (Figure 2).

Figure 2: The count of CleanTech projects by year



Source: Department of Industry, Innovation and Science (2016)

[4] See footnote 3.

In the CleanTech database each applicant describes the project and the facilities (and their locations) where the project is to take place and the estimated cost of the project. A percentage of up to half the project cost is then offered to the firm. Once the offer is taken, the project goes ahead and actual cost reports are regularly produced. The government pays the agreed percentage of actual costs up to a pre-determined ceiling in instalments as the project proceeds.

The progress of projects is monitored by the government to ensure that the grant is spent on the designated project and at the designated facility described in the initial submission. A facility might apply for more than one CleanTech grant to carry out multiple projects. Alternatively, a grant can be requested to treat multiple facilities.

3.3 Matched Data

The NGERS is an activity-level database, reporting emission and energy consumption for each activity at each facility (Table 9). For the matching, I aggregate emission and energy consumption to facility level. On the other hand, CleanTech is a project level database. Through careful examination of the projects, I manage to link each project to the facility or facilities the project is intended for.

The matches are not necessarily one-to-one. Some projects indicate that the grant will be used to treat multiple facilities. Not knowing how the funds will be alloted between the facilities, I am assuming that the total cost of project and the offered grant are equally divided. The value of projects does not play any key role in the empirical modelling, therefore, the simplifying assumption is inconsequential to the main findings.

There are also facilities that conduct multiple projects and receive separate grants for each one. These projects do not necessarily start and finish at the same time but mostly take place over the period 2012 to 2014. In case a facility is associated with multiple projects, I aggregate the cost of projects and the offered grants to a total per facility.

At this point, it is worth mentioning that not all projects from the CleanTech database can be matched to a facility in the NGERS. The reason is that several of the registered firms in the CleanTech database fall below the thresholds in the NGERS for mandatory reporting. Still, several of the facilities in the NGERS matched to the CleanTech projects are small but part of a larger parent firm.

The objective is to look at the reduction in emission intensity as a result of firms switching to cleaner technology. I also want to investigate whether those facilities with CleanTech grants show a technological shift above and beyond the average manufacturing facility without CleanTech grants. I will approach the issue by defining and comparing the emission production technology in 2011 (which I call period 1) versus that in 2014 (which I call period 2).

The CleanTech programme commenced on July 1, 2012. For that reason, I consider 2011 as the last year of status quo and use it as a benchmark. Year 2014 is the last year on which data is available.

In case, for any reason, a facility is not reporting in 2011 or 2014, I will use the facility's report in 2010 or 2013, respectively, to fill the gap where possible (142 facilities fall into this category).

The size and composition of the matched dataset is illustrated in Table 1, where each row lists the number of facilities in periods 1 and 2 by industry or by the state of operation. The table also lists the number of facilities with CleanTech projects. Some facilities reporting in period 1 are not reporting in period 2 or *vice versa* for one reason or the other. Those facilities will be dropped from the analysis as facilities must report in both periods for a proper assessment of changes that took place. This requirement limits the number of facilities that are used in the empirical exercises to 1,061.

Table 1: The count of facilities in the matched data by industry and jurisdiction

	Number of Facilities			
	Period 1		*Period 2*	
Industry	*Total*	*CleanTech*	*Total*	*CleanTech*
Food Products	420	43	469	51
Beverage and Tobacco	94	6	105	6
Textile, Leather, Clothing and Footwear	12	1	9	1
Wood Products	108	2	77	4
Pulp and Paper Products	83	0	78	9
Printing	26	5	25	5
Petroleum and Coal Products	66	4	47	3
Basic Chemicals	182	11	191	10
Polymer and Rubber Products	85	3	62	4
Non-metallic Minerals	170	10	156	12
Primary Metal Products	106	3	81	3
Fabricated Metal Products	107	5	131	10
Transport Equipment	70	3	64	3
Machinery and Equipment	35	2	27	2
Furniture and Other Manufacturing	34	2	30	0
State/Territory	*Total*	*CleanTech*	*Total*	*CleanTech*
Australian Capital Territory	12	1	13	1
New South Wales	404	34	422	42
Northern Territory	22	0	22	0
Queensland	347	15	327	19
South Australia	157	9	154	11
Tasmania	98	3	73	3
Victoria	386	30	360	36
Western Australia	172	8	181	11
Total number of facilities	*1,598*	*100*	*1552*	*123*

Source: NGERS and Department of Industry, Innovation, and Science

The counts show that food and beverage together are by far the largest group in the NGERS; about one third of facilities listed in the NGERS are food or beverage manufacturers. This disproportionate presence of the food industry in Australian manufacturing can explain the CleanTech's focus on food facilities. Accordingly, more than 40 per cent of the matched facilities with CleanTech projects are food or beverage manufacturers.

The counts also exhibit a concentration of facilities and CleanTech projects within the three most populated States in Australia, namely, New South Wales, Victoria, and Queensland. One also observes a small drop in the total number of reporting facilities from period 1 to period 2, which reduces the overlap to some extent. In the analysis that will follow a facility has to be observed in both periods.

Table 2 lists the descriptive statistics for energy consumption and emission across facilities that appear in both period 1 and 2. The deciles especially show that facilities are quite dispersed in size, measured in either energy consumption or emissions. There is also a substantial presence of small facilities as well as large ones. The contrast between the median and mean values especially shows that the size distributions are very skewed; the mean value is practically driven by a small number of very large facilities, whereas the median establishes that the data is mostly populated by smaller facilities. This distribution as a whole is very typical of size distribution of firms and establishments in Australia.

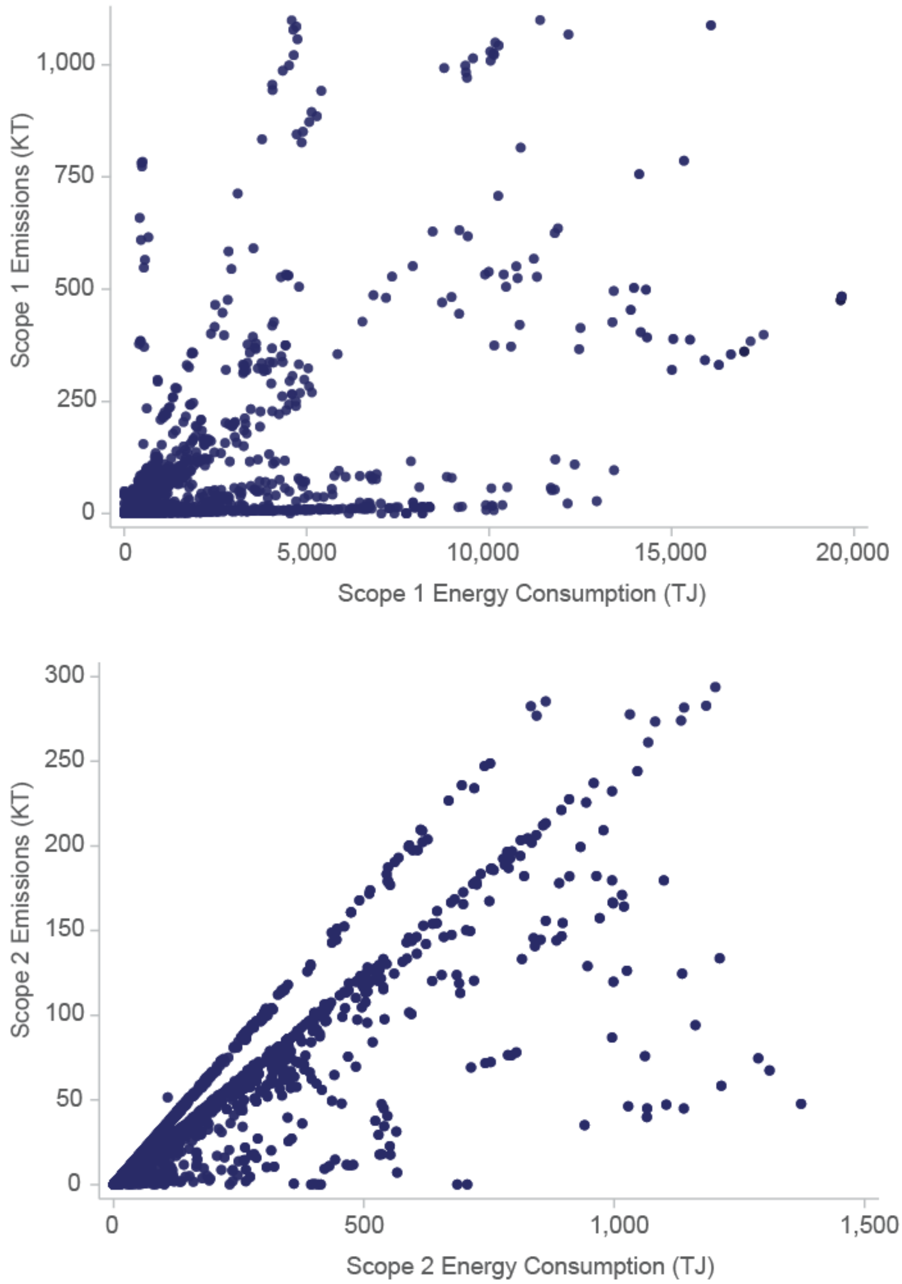
Table 2: Descriptive statistics of key variables in the balanced sample of facilities that appear in both periods

Variable	*Mean*	*Std.Dev.*	*10th Pctl.*	*Median*	*90th Pctl.*
Period 1					
ENERGY (TJ)	1,833.6	16,407.6	0.8	46.0	870.7
EMISSION (KT)	61.5	314.2	0.1	5.3	62.2
Period 2					
ENERGY (TJ)	1,746.8	15,952.2	0.3	38.7	836.9
EMISSION (KT)	69.1	622.0	0.0	4.5	50.1
Period 1 to 2					
Δ*ENERGY* (TJ)	-84.2	3,401.5	-76.4	-0.6	43.3
Δ*EMISSION* (KT)	7.6	493.9	-8.4	-0.3	1.8
Number of CleanTech facilities: 91					
					N=1,061

Source: NGERS

To better understand the relationship between energy consumption and emission in support of a production function model, I present Figure 3 where the energy consumption and emission of each observation in the data are plotted against each other for scope 1 (panel (a)) and scope 2 (panel (b)) reports. A notable feature of the plots is that they exhibit multiple *rays*. This pattern seems to be driven by the mix of technology – e.g. gas, coal, oil , or petroleum based – used by each manufacturing sub-division. For instance, in Figure 3(a) the upper ray is mostly populated by Non-metallic Mineral production facilities, whereas most chemical and metal production facilities are located around the middle ray.

Figure 3: The plot of facility-level energy consumption and emission by scope and using the pooled NGERS data



Note: The plots exclude extreme observations.

Source: NGERS

4. A Structural Approach

Let emission in manufacturing facility *j* controlled by parent firm *f* be produced according to the general production technology

$$EMISSION_{jf,t} = e^{c_t + i_{jft} + \epsilon_{jft}} ENERGY_{jf,t}^{a_t}, \quad t = 1,2. \tag{1}$$

In this function, *a* represents the returns to scale and *c* represents the level of efficiency in manufacturing. These parameters are allowed to vary from period 1 to period 2 in response to a sector-wide trend in the adoption of newer technology. Also note that, given the undesired nature of output, higher efficiency is implied by a lower value of *c*.

In view of Figure 3, efficiency in a facility can also depend on its sub-division. For that reason, a set of industry effects, i_{jft} are included. The disturbance term, ϵ_{jft}, accounts for any idiosyncratic difference in the efficiency of facilities not captured by the prevailing mode of technology or industry effects.

Putting production function (1) in logs and taking differences yields

$$\begin{aligned} \Delta emission_{jf} &= \Delta c + a_2 energy_{jf,2} - a_1 energy_{jf,1} + \iota_{jf} + \varepsilon_{jf} \\ &= \Delta c + a_2 \Delta energy_{jf} + \Delta a\ energy_{jf,1} + \iota_{jf} + \varepsilon_{jf}, \end{aligned} \tag{2}$$

where lower case names denote variables in logs, and Δ operator indicates the change from period 1 to period 2. In equation (2), $\iota_{jf} = \Delta i_{jft}$ accounts for industry-specific change in efficiency and $\varepsilon_{jf} = \Delta \epsilon_{jft}$.

To study the impact of CleanTech, the production function (1) is extended to include additional changes in period 2 resulting from the implementation of the programme. This production function only applies to those facilities with CleanTech projects and is written as

$$EMISSION_{jf,2} = e^{c_2 + \delta_c + i_{jft} + \epsilon_{jf2}} ENERGY_{jf,2}^{a_2 + \delta_a}, \tag{3}$$

where δ_a and δ_c are the parameters associated with the impact of CleanTech above and beyond the sector-wide trend. Again, putting in logs and taking differences yields

$$\begin{aligned} \Delta emission_{jf} &= \Delta c + \delta_c + (a_2 + \delta_a) energy_{jf,2} - a_1 energy_{jf,1} + \iota_{jf} + \varepsilon_{jf} \\ &= \underbrace{a_2 \Delta energy_{jf}}_{\text{Change in Scale}} + \underbrace{\Delta c + \Delta a\ energy_{jf,1}}_{\text{Sector Technology Shift}} + \underbrace{\delta_c + \delta_a energy_{jf,2}}_{\text{CleanTech}} + \iota_{jf} + \varepsilon_{jf}. \end{aligned} \tag{4}$$

The first term above describes the change in emission production as a result of change in energy consumption, keeping the emission technology fixed. A large part of reduction (or increase) in emission is in fact not caused by a change in technology but simply due to a change in the scale of energy consumption. For a more accurate measurement of policy effect, this component needs to be factored out.

The second component models the part of change in emission that is driven by a sector-wide trend in the adoption of cleaner technologies, keeping energy consumption fixed.

The last component specifically models the premium that carrying out a CleanTech project within the facility could offer compared to unassisted facilities. This last component will be absent for all facilities that do not receive any CleanTech grant.

Putting (2) and (4) together leads to the complete specification below:

$\Delta emission_{jf} = a_2 \Delta energy_{jf} + \Delta c + \Delta a\ energy_{jf,1} + \left(\delta_c + \delta_a energy_{jf,2}\right) \times CleanTech_{jf} + \iota_{jf} + \varepsilon_{jf}$. (5)

In this equation, *CleanTech* is a dummy variable that indicates whether facility *j* of firm *f* received CleanTech grant(s). ι_{jf} is modeled by a set of industry dummies for each manufacturing sub-sector.

Equation (5) is a linear form that can be simply estimated using OLS. However, the estimation of production functions is often beset by endogeneity issues insofar as firms can promptly react to idiosyncratic shocks by adjusting input factors. In this case, it is possible that positive(negative) shocks force firms to react by reducing (increasing) energy consumption in a facility, generating some correlation between ε_{jf} and $energy_{jf,2}$ (in turn, $\Delta energy_{jf}$).

Olley & Pakes (1996) and Blundell & Bond (2000) each propose a fix to the above problem by using capital investment or lags of variables as instruments in the estimation of Total Factor Productivity. Due to limitations in the number of variables and the available years, these approaches are infeasible in the current setting. Instead, I explore the potential for biases by focusing on a subset of observations where the endogeneity is minimised.

The premise is that endogeneity has to be the strongest within multi-facility firms. These firms have the flexibility to quickly redistribute business activity among their facilities when some of those facilities are hit by worse shocks than the others; thus, the firm can quickly mitigate shocks without incurring any major cost. Single-facility firms, on the other hand, lack this flexibility, and energy consumption in these firms has to do more with demand than shocks. Estimating (5) by restricting the sample to single-facility firms or firms with very few facilities can provide a hint on the direction and magnitude of the bias.

5. Empirical Findings

5.1 General Results

The OLS estimates of (5) are reported in Table 3 in a nested order to first test for the importance of CleanTech as a programme. Column (1) in the table reports the estimated coefficients without the CleanTech components. Those components are added in column (2), where the full model is estimated. It is likely that strategic decisions are made at headquarters and affect all facilities belonging to the same parent firm to some degree. For this reason, the standard errors in every column are clustered by parent firms.

First of all, using the log likelihoods reported in columns (1) and (2), one finds that the likelihood ratio statistic between the two models is 7.2 with a a p-value of 0.027 (using a χ^2_2), hence, CleanTech appears to have a significant impact on the estimates.

The industry effects are not reported in Table 3, but the collective F-statistic for the industry dummies in column (2) is significant at the 10 per cent level. The estimated effects are, however, rather mixed and do not point to any specific pattern.

Table 3: Estimates of model (5)

	Dependent: Δemission				
Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*
a_2	0.710***	0.712***	0.718***	0.641***	0.708***
	(0.057)	(0.057)	(0.055)	(0.082)	(0.059)
Δc	-0.125***	-0.129***	-0.128***	-0.200**	-0.207***
	(0.031)	(0.030)	(0.031)	(0.090)	(0.048)
Δa	0.006	0.007	0.008	0.020*	0.002
	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)
δ_c		0.436**	0.371**	0.572*	1.639**
		(0.201)	(0.176)	(0.301)	(0.809)
δ_a		-0.084**	-0.080**	-0.097**	-0.180*
		(0.037)	(0.037)	(0.041)	(0.102)
Method	OLS	OLS	OLS	OLS	IV
Sample	All	All	Completed Projects	#Facility≤3	All
Adj. R^2	0.729	0.731	0.737	0.628	0.735
F	16.27	30.68	29.14	14.08	17.63
Log Likelihood	-643.7	-640.1	-623.5	-46.2	-616.8
N	1,061	1,061	1,037	151	1,016

Note: In column (3) sample excludes CleanTech facilities with no completed projects. In column (4) only firms with at most three facilities are included. Numbers in parentheses are standard errors clustered by parent firm. ***, **, and * denote 1%, 5% and 10% significances, respectively. A set of industry dummies are also included but not reported.

Source: Author's own calculations.

Focusing on column (2), a_2 accounts for the change in emission caused by a change in the level of energy consumption keeping technology fixed. The estimated value is statistically significant. It also points out that a substantial part of the change in emission can in fact be accounted for by the change in energy consumption alone.

The next two coefficients are associated with a sector-wide change in the emission production technology. Per these findings, the emission technology seems to have become more efficient over the period. The estimate for Δc is negative and statistically very significant. Change in returns to scale, coefficient for Δa, is very small and statistically insignificant.

The rest of the coefficients represent the effect of CleanTech grants above and beyond the sector-wide trend. The estimates for both δ_c and δ_a, again, corroborate that CleanTech had a statistically significant effect on the facilities that utilised the grants. However, the direction of the effect is such that it moves the technology in the opposite direction to that of the general technological trend. More specifically, the CleanTech projects have reduced the returns to scale in the production function at the expense of making production more inefficient (i.e. increasing *c*).

Considering this pattern, it seems that large facilities must have benefited from CleanTech in a very peculiar way. The drop in returns to scale effectively introduces a cap on emissions among large facilities without making the technology any more efficient. In Section 5.2, I will come back to this issue with more details.

In columns (3) and (4) I conduct two robustness tests. In column (3), I estimate model (5) by leaving out those facilities where no CleanTech project is completed by 2014. This is a test to make sure that including facilities with progressing CleanTech projects is not distorting the results. In Column (4), I estimate the model using only firms with three or fewer facilities to mitigate endogeneity and detect the direction of the related bias.[5]

Results in column (3) confirm that dropping CleanTech facilities with no completed projects does not have any substantial effect on the implications, therefore, the results are robust to this type of sample restriction. In column (4), one observes that after restricting the sample to firms with three or fewer facilities there is no change in the qualitative implications; as a matter of fact, the results get stronger. In other words, the results here are under-estimation and not over-estimations.

It must be noted that the estimated CleanTech effects so far represent the treatment effect *on the treated*. It is possible that facilities that received the CleanTech grants are a selected group; for instance, those facilities demonstrating the inability to go forth with the project without assistance. Such selection will introduce a bias into the estimates. One might wonder how results would be affected in case the facilities were part of an experimental treatment where participants are randomly assigned.

Following a simple suggestion by Vella & Verbeek (1999), I investigate by constructing an instrumental variable. I first predict the probability of CleanTech using a Probit estimation of *CLEANTECH* on $energy_{jf,1}$ and $\Delta energy_{jf,1}$ and one exogenous variable. I then re-estimate (5) using this probability as the instrument for *CLEANTECH*. For the exogenous variable I am using the number of government employees in the renewable energy sector in each state averaged over the years 2009 to 2011 (ABS cat.no.4631.0). Antonioli et al. (2016) show local spillovers from such activity, and a higher level of local government involvement would contribute to the spillover.[6]

Column (5) in the table reports these last results. There is no qualitative difference between these results and those from column (2).

[5] Restricting the sample to firms with one or two facility generates similar results, but the statistical significance gets weaker owing to the small sample size. Note that the median number of facilities in the matched dataset is 15.

[6] The estimated Probit model is

$$Prob[CleanTech] = \Phi(-2.69^{***} + 0.001^{*}GOV + 0.115\Delta energy + 0.182^{***}energy_1 + \text{Industry Effects}).$$

Φ is the standard normal cumulative distribution function. * and *** denote 10% and 1% significance levels.

The estimated coefficients discussed above point to interesting shifts in the emission technology. However, the fact that the production function is driven by two parameters, namely, efficiency and returns to scale, makes it non-trivial to answer the fundamental question as to whether technological changes – and CleanTech in particular – resulted in a drop or an increase in emissions. In this part of the analysis, I use the estimated figures from column (2) of Table 3 to separately predict the change in emissions caused by the change in the scale of energy usage, sector-wide technology, and CleanTech.

For each observation, I compute the exponential of the change predicted for each undersigned component in (3) keeping all else fixed. The resulting number is the proportion of emissions in period 2 to 1. I then convert this number into percentage change by subtracting one and multiplying by 100. Table 4 reports the mean values for each factor. The distributions are shown in Figure 4.

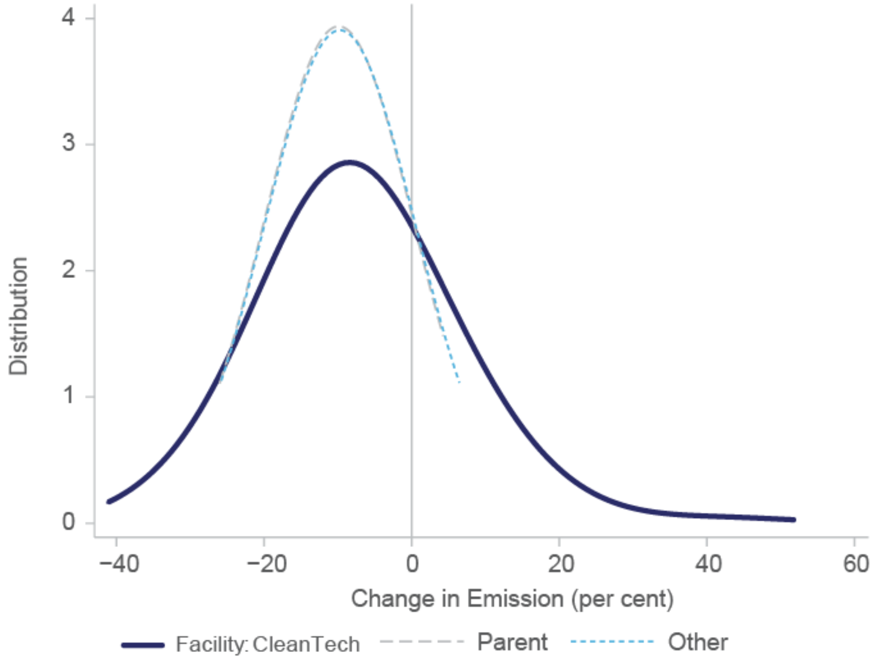
Table 4: The average percentage change in emissions caused by scale and technological factors

		Change in Emissions (per cent)			
Type of Facility	*Scale*	*Sector-wide Technology*	*CleanTech*	*Fulll Technology*	*N Facility*
CleanTech	-1.4	-8.7	2.2	-6.8	90
Parent	8.2	-9.9		-9.9	395
Other	6.0	-9.8		-9.8	576
Total	6.2	-9.7	2.2	-9.6	1,061

Note: Full technology accounts for contributions from both sector-wide and CleanTech technological changes.

Source: Author's own calculations

Figure 4 The distribution of change in emissions in facilities caused by the technological shift



Note: The distributions are estimated using a Gaussian kernel with bandwidth 0.1 for the predicted values.

Source: Author's own calculations

I am making a distinction between facilities that directly receive CleanTech grants versus facilities with no CleanTech projects that, nevertheless, are controlled by a parent with other CleanTech facilities. Watching for differences among these two types of facilities has the potential to further highlight the direct and indirect impacts of CleanTech. Facilities belonging to parents with no CleanTech projects are listed separately.

For each type of facility, the average change in emission is reported separately for change in scale, change in sector-wide technology, and the additional change associated with CleanTech where available. An extra column lists the full contribution of technological change by putting CleanTech and sector-wide technological changes together for easier cross-group comparisons.

The first interesting observation is that neither the table of means nor the distributions show any major difference between non-CleanTech facilities with CleanTech parents and other non-CleanTech facilities, whereas there is a substantial gap between CleanTech facilities and every other facility. This pattern suggests a lack of intra-firm diffusion and much less inter-firm spill-overs. I will look at this issue in more details in Section 6 where I define a few indexes of exposure to CleanTech programme and test them for any implied effects.

Overall, there has been an expansion in the level of energy consumption at the same time that technology has become cleaner. Specifically, the emission has dropped by 9.7 per cent as a result of sector-wide technological shift. The total emission in 2011 reported in the NGERS is about 115.27 megatonnes, therefore, the change translates to about 11.2 megatonnes reduction in carbon emissions or the equivalent over the period.

In line with the findings in Table 3, the CleanTech facilities on average show a smaller technological effect. The average drop in emissions as a result of technological shift among these facilities is 6.8 per cent, which falls short of that achieved by other facilities by about 2.9 points. Instead, the CleanTech facilities see a drop in their emissions as a result of lower energy consumption. In general, the drop in energy consumption can be caused by a contraction in business activity or by switching to less energy-intensive technologies. In the case of CleanTech facilities, it is likely that the latter is the main reason.

Accordingly, Figure 4 demonstrates that the centre of gravity for the distribution of CleanTech facilities lies slightly to the right of that of the other facilities. Besides, the distribution of CleanTech facilities is more dispersed than that of the other facilities. There are CleanTech facilities that realise more technologically driven emission reduction than the average. There are also CleanTech facilities whose technology seems to regress. These latter facilities are likely those that are more concerned with managing their energy intensity than with clean technology.

5.2 CleanTech and Facility Size

In this section I investigate the earlier conjecture that the impact of CleanTech is size-dependent. For this purpose, I allow the CleanTech effect in (5) to have extra terms that depend on size. I use the energy consumption of facilities in period 1 as the measure of facility size.

The estimated coefficients are reported in Table 5. Column (1) in the table is the same as column (2) in Table 3 to facilitate comparisons. In column (2), the interactions with size are added.

Table 5: Estimates of model (5) using size-dependent CleanTech terms

	Dependent: *Δemission*		
Variable	*(1)*	*(2)*	*(3)*
a_2	0.712***	0.723***	0.713***
	(0.057)	(0.052)	(0.056)
Δc	-0.129***	-0.119***	-0.126***
	(0.030)	(0.031)	(0.031)
Δa	0.007	0.007	0.007
	(0.007)	(0.007)	(0.007)
δ_c (CleanTech)	0.436**	-0.408**	-0.574
	(0.201)	(0.205)	(0.675)
δ_a (CleanTech)	-0.084**	-0.464**	0.090
	(0.037)	(0.214)	(0.125)
$\delta_c \times \log(Size)$		0.657***	0.161
		(0.175)	(0.116)
$\delta_a \times \log(Size)$		-0.023**	-0.027
		(0.010)	(0.019)
Size	None	$ENERGY_1$	*GRANT*
Adj. R^2	0.731	0.740	0.731
F	30.68	25.31	26.99
Log Likelihood	-640.1	-620.5	-639.0
N	1,061	1,061	1,061

Note: Numbers in parentheses are standard errors clustered by parent firm. *** and ** denote 1% and 5% significances, respectively. A set of industry dummies are also included but not reported.

Source: Author's own calculations.

The model statistics show that the estimates in column (2) are a significant improvement over those of column (1); the likelihood ratio test yields a high level of significance and the added coefficients show statistical significance.

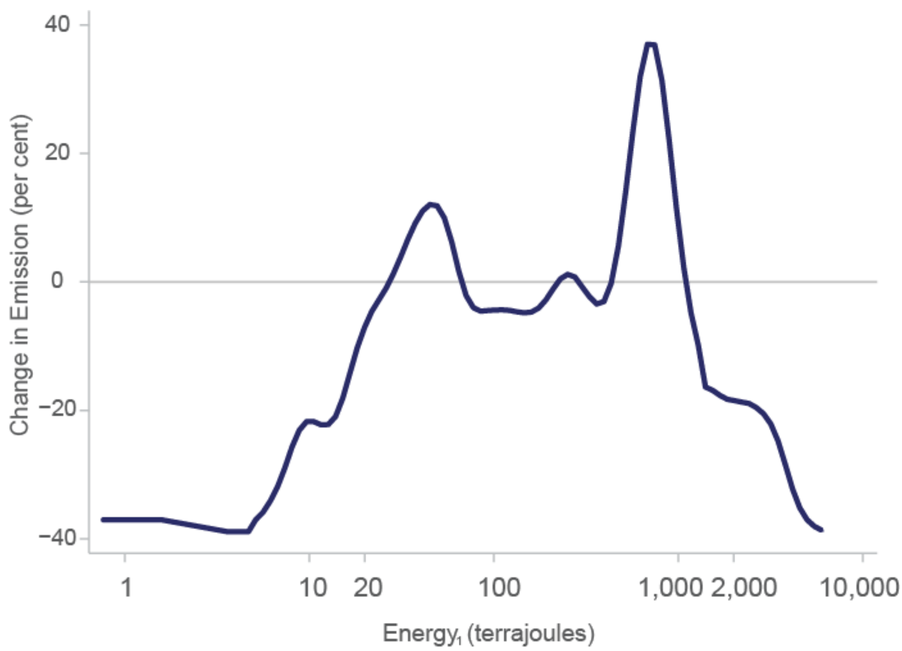
Using the estimation in column (2) as the preferred model, one infers that the impact of CleanTech is indeed size-dependent. For the smallest facilities in the sample – in terms of energy consumption – both the efficiency and the returns to scale of the production function are improving. As size grows, CleanTech facilities experience less improvement in efficiency, yet returns to scale constantly drops with an increase in size. As for the last effect, it is not clear whether CleanTech is conducive to a drop in emission or not.

In column (3) of the table, I use the size of the CleanTech grant as the indicator of size. It is useful to know whether larger grants were used to invest in clean technology. However, the likelihood ratio test and the significance of the estimated coefficients refute the hypothesis that the size of the grant is a determining factor.

Coming back to model (2), I will use those coefficients to predict the percentage emission reduction caused by the technological impact of CleanTech in the same way as in Section 5.1 The result will clarify how the relationship is affected by the combination of changes in efficiency and scales to return as size changes. I find the relationship using a kernel regression that estimates the average reduction caused by the CleanTech effect as a function of energy consumption (i.e. size). I am leaving out the sector-wide technological shift out of this picture as it is independent of size in this model.

Figure 5 shows the estimated relationship. One observes that two size groups among CleanTech facilities are on average substantially reducing emission by investing in clean technology. These two groups are small facilities (almost 20 terrajoules of energy consumption and lower) and very large facilities (larger than one petajoules of energy consumption). Facilities in the middle of the range on average do not experience much emission reduction pertaining to technological shift.

Figure 5: The average change in emissions in CleanTech facilities due to technological factors as a function of energy consumption in period 1



Note: Using a kernel regression with Gaussian kernel and a bandwidth of 0.25 for log of energy consumption.

Source: Author's own calculation

The pattern, again, confirms that size is a determining factor in how the CleanTech grants affected facilities; besides, the effect is non-monotonic. To further reason that facilities only focused on either clean technology or energy intensity but not both, I present Table 6. The table lists the correlation coefficients between the predicted effects of scale and technology components.

Table 6: The correlation coefficient between the scale and technology components predicted using model (2) in Table 5 within different size groups

Correlating	*$ENERGY_1$ (TJ)*				
Scale with non-CleanTech	*≤ 20*	*∈]20,100]*	*∈]100,500]*	*∈[500,1000]*	*>1000*
Technology	-0.111**	-0.083	-0.055	0.057	0.125
N	386	221	235	36	93
CleanTech					
Technology	-0.732	-0.857***	-0.625***	-0.900***	-0.804*
CleanTech-component	-0.749	-0.857***	-0.625***	-0.900***	-0.793*
N	5	20	48	11	6

Source: Author's own calculations.

The table reveals two things. First, among the non-CleanTech facilities in the mid-range of size there is no clear relationship between the two components. The relationship is, however, negative and statistically significant among CleanTech facilities. Almost all of that correlation is driven by CleanTech itself. In other words, CleanTech facilities in this range invested the grant either to adopt cleaner technology or to reduce energy consumption but not both.

Second, the majority of CleanTech facilities are within 20 terrajoule and one petajoule range. However, those few CleanTech facilities outside this range took a decisive direction. Assuming continuity, one deduces that the proportion of CleanTech facilities that use the grants to adopt cleaner technology increases as energy size approaches the distribution tails. Likewise, the proportion of CleanTech facilities focused on reducing energy intensity is the highest around the mid point.

6. Exposure Impact of CleanTech

Apart from affecting the facilities that received grants, CleanTech can also have a broader impact by intensifying competition or providing lessons that urge other facilities to increase their investment in clean technology. This effect can be the broader impact of the CleanTech programme. In what follows, I will look at this issue by introducing a few measures of *exposure* to CleanTech.

6.1 Facilities exposed to CleanTech

I consider two types of exposure for more accurate results. The first type of exposure affects those facilities that did not receive CleanTech grants, nevertheless, got exposed to CleanTech through their parent or holding company controlling facility or facilities with CleanTech projects. In case the decision to switch to a cleaner technology is made at the top levels of management, the parent firm could use the lessons learned from the implementation of a CleanTech project in one or more of its facilities to improve operation in the other facilities it controls. To test this hypothesis, I introduce the dummy variable, *Parent*, that is equal to one if a facility did not receive CleanTech funding directly but belongs to a parent company with one or more CleanTech facilities. *Parent* is set to zero otherwise.

The second type of exposure pertains to facilities with parent firms that have no CleanTech grants across any of their facilities. One can hypothesize that being geographically co-located with another facility that does carry out CleanTech projects might have some influence on the facility's or its parent's decision to double their effort in switching to cleaner technology. To account for this type of *geographic* exposure, I define the following measure

$$Exposed_{jf}^{Num} = \sum^{j\prime,j\prime\neq j,f\prime\neq f} \frac{CleanTech_{j\prime f\prime}}{d_{j,j\prime}^2}. \qquad (6)$$

This measure of exposure basically finds the weighted number of projects in the geographic vicinity of facility *j* where the weights are the inverse of squared distances between facility *j* and the other CleanTech facilities. I set the measure equal to zero if a facility or its parent has any CleanTech projects. Therefore, this measure, *Parent*, and *CleanTech* are mutually exclusive. Using this measure, one can test whether the mere introduction of a CleanTech project in an area had any influence on how other facilities behaved. In Australia, firms can be thousands of kilometers apart, therefore, I use the Haversine formula to compute the physical distance between every pair of facilities.[7]

I also define a second measure of exposure that also accounts for the size of projects, in case larger projects received more publicity, hence, had larger influence. This measure is defined as

$$Exposed_{jf}^{Cost} = \log\left(1 + \sum_{j\prime,j\prime\neq j,f\prime\neq f} \frac{\text{Total Project Cost}_{j\prime f\prime}}{d_{j,j\prime}^2}\right). \qquad (7)$$

The term inside the parentheses is one plus the accumulated cost of all CleanTech projects in the vicinity of facility *j*. The log is taken to control for extreme values. As in (6), the measure is set equal to zero if a facility or its parent has any CleanTech projects.

The implementation of these exposure effects in the production function is identical to that of the CleanTech in (5). Therefore, following the same procedure, one can write an extended version of (5), which gives:

$$\Delta emission_{jf} == a_2 \Delta energy_{jf} + \Delta c + \Delta a\ energy_{jf1} + (\delta_c^{CleanTech} + \delta_a^{CleanTech} energy_{jf2}) \times CleanTech_{jf} + (\delta_c^{Parent} + \delta_a^{Parent} energy_{jf2}) \times Parent_{jf} + (\delta_c^{exposed} + \delta_a^{exposed} energy_{jf2}) \times Exposed_{jf} + \iota_f + \epsilon_{jf}, \quad (8)$$

In this specification, *Exposed* is either of the measures define in (6) or (7).

The estimated coefficients are listed in Table 7 columns (1) and (3). Column (1) lists the estimates for the restricted model with no exposure effects. I will use this result to test for the significance of the added exposure terms.

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[7] Specifically, let the coordinates of firms *j* and *j'* be (x_j,y_j) and ($x_{j'}$,$y_{j'}$), then

$$d_{j,j'} = 2R\arcsin\left(\sqrt{\sin^2\left(\frac{y_j - y_{j'}}{2}\right) + \cos(y_j)\cos(y_{j'})\sin^2\left(\frac{x_j - x_{j'}}{2}\right)}\right),$$

in which *R*=6371.009*km* is the average radius of the earth.

Table 7: OLS estimates model (8)

Variables	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*
a_2	0.71***	0.71***	0.72***	0.80***	0.80***	0.80***	0.85***	0.85***	0.84***
	(0.06)	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.05)	(0.05)
Δc	-0.13***	-0.14***	-0.24***	-0.08**	-0.05	-0.06	-0.09***	-0.06	0.02
	(0.03)	(0.04)	(0.07)	(0.04)	(0.04)	(0.07)	(0.03)	(0.04)	(0.06)
Δa	0.01	0.01	0.02	0.01	0.00	-0.00	0.02***	0.02**	0.01
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
δ_c	0.44**	0.45**	0.55**	0.40**	0.38**	0.39**	0.29	0.25	0.18
	(0.20)	(0.21)	(0.22)	(0.18)	(0.19)	(0.19)	(0.20)	(0.20)	(0.21)
δ_a	-0.08**	-0.08**	-0.10**	-0.07*	-0.07*	-0.07	-0.07	-0.06	-0.05
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
$\delta_c(parent)$		0.01	0.11		-0.01	0.00		-0.07*	-0.15**
		(0.06)	(0.09)		(0.06)	(0.08)		(0.04)	(0.07)
$\delta_a(parent)$		0.00	-0.01		-0.01	-0.01		0.01	0.02
		(0.02)	(0.02)		(0.03)	(0.03)		(0.01)	(0.01)
$\delta_c(exposed)$		0.03	0.02**		-0.09*	-0.00		-0.02	-0.02
		(0.04)	(0.01)		(0.05)	(0.01)		(0.04)	(0.01)
$\delta_a(exposed)$		(0.04)	(0.01)		(0.05)	(0.01)		(0.04)	(0.01)
		(0.01)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
Exposure	None	Num	Cost	None	Num	Cost	None	Num	Cost
Adj. R^2	0.73	0.73	0.73	0.69	0.69	0.69	0.84	0.84	0.84
F	30.7	31.9	29.9	31.1	34.1	31.2	65.4	72.1	76.4
Log Likelihood	-640.1	-639.8	-637.4	-842.7	-841.2	-842.0	-299.0	-296.3	-293.1
N	1,061	1,061	1,061	931	931	931	1,025	1,025	1,025

Notes: Numbers in parentheses are standard errors clustered by parent firms. ***, ** and * denote 1, 5, and 10 per cent significances, respectively. A set of industry dummies are included but not reported.

Sources: Author's own calculations

The estimates for parent or geographic exposure in columns (2) and (3) do not point to any remarkable effect. The likelihood ratio test between these models and the restricted version in column (1) does not yield any statistical significant either.

I further explore whether exposure has only been a driving force for a certain type of technology, that is, certain scope of emission. In columns (4) to (9) of Table 7, I report the estimation results restricting the dependent and the explanatory variables to scope 1 or scope 2 emissions and energy only.

Again, the coefficients pertaining to exposure effects are mostly insignificant statistically. In the case of scope 1 emission, likelihood ratio tests do not return any statistically significant values. For scope 2 emission, likelihood ratio test is only significant – and at 2.5 per cent level – when exposure is measured in grant amount.

Accordingly, facilities exposed to CleanTech projects through their parents do show some efficiency improvement in Scope 2 emissions. No such impact can be detected for geographic exposure as those coefficients are all statistically insignificant. This last result particularly suggests that the size of projects matters and larger projects, measured in their total cost, tend to generate some ripple effect where a number of small projects would have failed to make an impression.

The exposure effect being constrained to scope 2 emission also suggests that firms and facilities exposed to CleanTech were probably looking for quick and inexpensive ways to reduce energy costs.

6.2 Geographic segmentation and CleanTech exposure

In view of the results of the last section, I also hypothesise that the exposure effect of CleanTech programme might have to do with geographic segmentation of production. Firms that are highly segmented – e.g. operate a lot of facilities in various and possibly remote locations – could experience some detachment between their headquarters where the decisions are made and the facility floors where observations are made. The more the detachment, the weaker the reaction to exposure to CleanTech programme. To test whether this is the case, I re-estimate the coefficients in (8) but by weighting each facility by the inverse of number of manufacturing facilities that the parent controls. In this way, I am putting more emphasis on firms with lower number of facilities and less operational segmentation.

Alternatively, and to test for geographic remoteness, I define another weighting variable which is the following Herfindahl index:

$$H_{jf} = \sum^{s} h_{jfs}^{2}, \qquad (9)$$

where *h* is the share of facilities belonging to firm *f* located in State *s*. If all facilities belonging to a firm are located within the same State, then *H*=1; otherwise, *H*<1 depending on how facilities are distributed between different States. I will then do an OLS estimation using *H* as observation weights. Again, this weighting puts more emphasis on firms whose operation is mostly concentrated within the same State.

Table 8: Weighted OLS estimates of model (8) using the invesre of number of facilities or Herfindahl Index as observation weights

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
a_2	0.701***	0.726***	0.709***	0.770***	0.636***	0.732***
	(0.058)	(0.050)	(0.085)	(0.066)	(0.131)	(0.079)
Δc	-0.288**	-0.256***	-0.026	-0.063	0.501**	0.200*
	(0.116)	(0.074)	(0.131)	(0.085)	(0.219)	(0.110)
Δa	0.024	0.019	-0.003	-0.001	-0.083*	-0.020
	(0.018)	(0.013)	(0.019)	(0.015)	(0.045)	(0.022)
δ_c *(CleanTech)*	0.728***	0.609***	0.673*	0.530**	-0.052	0.434
	(0.235)	(0.217)	(0.407)	(0.237)	(0.461)	(0.410)

Variable	*(1)*	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
δ_a *(CleanTech)*	-0.121***	-0.108**	-0.104*	-0.093**	-0.008	-0.111
	(0.038)	(0.042)	(0.063)	(0.045)	(0.100)	(0.089)
δ_c *(Parent)*	0.104	0.073	-0.055	-0.022	-0.698**	-0.325**
	(0.140)	(0.090)	(0.153)	(0.096)	(0.300)	(0.140)
δ_a *(Parent)*	-0.002	0.000	0.005	0.004	0.141**	0.061**
	(0.026)	(0.019)	(0.029)	(0.023)	(0.063)	(0.028)
δ_c *(Exposed)*	0.031	0.027**	-0.028	-0.005	-0.107**	-0.045**
	(0.019)	(0.011)	(0.025)	(0.014)	(0.046)	(0.021)
δ_a *(Exposed)*	-0.002	-0.002	0.007**	0.004	0.020**	0.008*
	(0.003)	(0.002)	(0.004)	(0.003)	(0.008)	(0.004)
Weight	1/# fac.	H	1/# fac.	H	1/# fac.	H
Adj. R^2	0.679	0.729	0.551	0.640	0.795	0.786
F	17.31	20.28	10.91	19.26	19.29	26.63
N	1,061	1,061	931	931	1,025	1,025

Note: Numbers in parentheses are standard errors clustered by parent firms. ***, ** and * denote 1, 5, and 10 per cent significances, respectively. A set of industry dummies are included but not reported.

Source: Author's own calculations

Each of the weighted OLS estimates are reported in Table 8. For these estimations, I am using the exposure measure in (7) since it is the only measure that has been shown to have some statistical significance.

Comparing coefficients in this table to those from Table 7 demonstrates that, again, scope 2 technology is the only area that is being impacted by exposure to large CleanTech projects. More importantly, the estimated coefficients in this case are larger in magnitude and statistically more significant. Consequently, geographic segmentation matters. Facilities tend to react more strongly to CleanTech projects when the parent firm is less segmented and more concentrated geographically.

7. Conclusion

The advantages and disadvantages of government emission-related regulations and intervention in the clean technology market are still a matter of research. In this paper, I look at the Clean Technology Investment programme through the lens of a time-varying production function for emission. The main purpose is to focus on the role of these initiatives in the adoption of cleaner technologies.

Using the production function, I manage to isolate the reduction in emission caused by the shift to clean technology. Comparing the change in manufacturing from 2011 to 2014 consistently shows that emission technology spontaneously became cleaner to the extent that consuming the same amount of energy now generates about 10 per cent lower emissions.

The role of the CleanTech programme in the adoption of cleaner technology has a size-dependent nature: smaller and larger manufacturing facilities invested more than the average into clean technology. A larger proportion of CleanTech facilities in the mid-size range opted to reduce energy intensity instead.

The study also detects a broader impact of the programme on facilities that did not receive CleanTech grants but were exposed to other facilities that did. However, this exposure effect is mostly manifested as a change in scope 2 emission technology – which is mostly electricity consumption. Not every facility responded to being exposed either. The findings show that segmented firms, with many facilities across different States, had a harder time assimilating the exposure effects, whereas firms with more concentrated operations responded more effectively. One can conjecture that the proximity between the operations and the headquarter or having a strong feedback line from operations to headquarter is a crucial factor in assimilating field observations, such as the implementation of a CleanTech project, into the decision making process.

Appendix A A NGERS Sample Facility Report

A mock sample of activity report by facilities in the NGERS is shown in

Table . Facilities report the mix of fuel and other energy sources they have consumed with energy and emissions associated with each activity. The table only shows a portion of the activity report pertaining to the type of energy sources. Other information in the activity report includes geographic coordinates of the facility, the parent firm, the state of operation, and the industry group.

Table 9: A mock sample of NGERS activity report.

Year	*Facility ID*	*Scope*	*Activity*	*Energy(GJ)*	*Emission(T)*
2011/12	12345	1	Black Coal - combustion	17,932.4	4,101.0
2011/12	12345	1	Diesel Oil - combustion	5,441.1	692.2
2011/12	12345	1	Gasoline - Transport	341.7	77.4
2011/12	12345	1	Fugitive gases	0	932.8
2011/12	12345	1	Methane release from wastewater handling	0	470.2
2011/12	12345	2	Coal generated electricity	2,452.9	724.3
2011/12	12345	2	Gas generated electricity	889.1	108.8
2011/12	12345	2	Solar electricity	1,117.0	0

Source: Department of Industry, Innovarion and Science (2016)

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